US 20200176114A1

(19) **United States**

(12) **Patent Application Publication** (10) **Pub. No.: US 2020/0176114 A1**

BADAWI et al. (43) **Pub. Date: Jun. 4, 2020**

(54) **SYSTEM AND METHOD FOR PROVIDING A LAYER-BASED PRESENTATION OF A MODEL-GENERATED PATIENT-RELATED PREDICTION**

(71) Applicant: **KONINKLIJKE PHILIPS N.V.**, EINDHOVEN (NL)

(72) Inventors: **OMAR BADAWI**, Lutherville Timonium, MD (US); **PAMELA JAYNE AMELUNG**, CLARKSVILLE, MD (US); **SUNIL SWAMI**, BALTIMORE, MD (US); **XINGGANG LIU**, BALTIMORE, MD (US); **XI GAO**, BALTIMORE, MD (US); **Erkan Hassan**, Baltimore, MD (US)

(21) Appl. No.: **16/613,007**

(22) PCT Filed: **May 25, 2018**

(86) PCT No.: **PCT/EP2018/063787**

§ 371 (c)(1),
(2) Date: **Nov. 12, 2019**

Related U.S. Application Data

(60) Provisional application No. 62/512,361, filed on May 30, 2017.

Publication Classification

(51) **Int. Cl.**

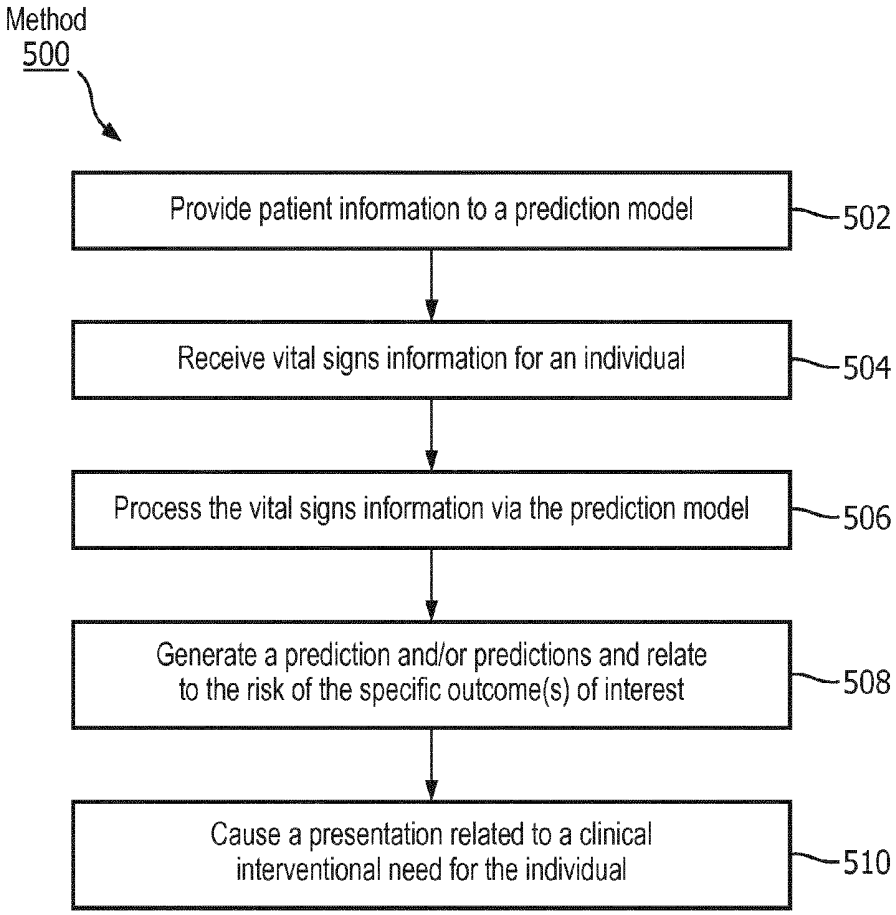
G16H 50/20	(2018.01)
G16H 40/63	(2018.01)
A61B 5/00	(2006.01)
G16H 50/30	(2018.01)

(52) **U.S. Cl.**

CPC ***G16H 50/20*** (2018.01); ***G16H 40/63*** (2018.01); ***A61B 5/0002*** (2013.01); ***G16H 50/30*** (2018.01); ***A61B 5/7275*** (2013.01)

(57) **ABSTRACT**

The present system is configured to provide patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients. The system is configured to receive vital signs information for one or more vital signs of an individual. The system is configured to process, via the trained prediction model, the vital signs information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features. The system is configured to cause a presentation related to a clinical intervention need for the individual based on the output of the model.



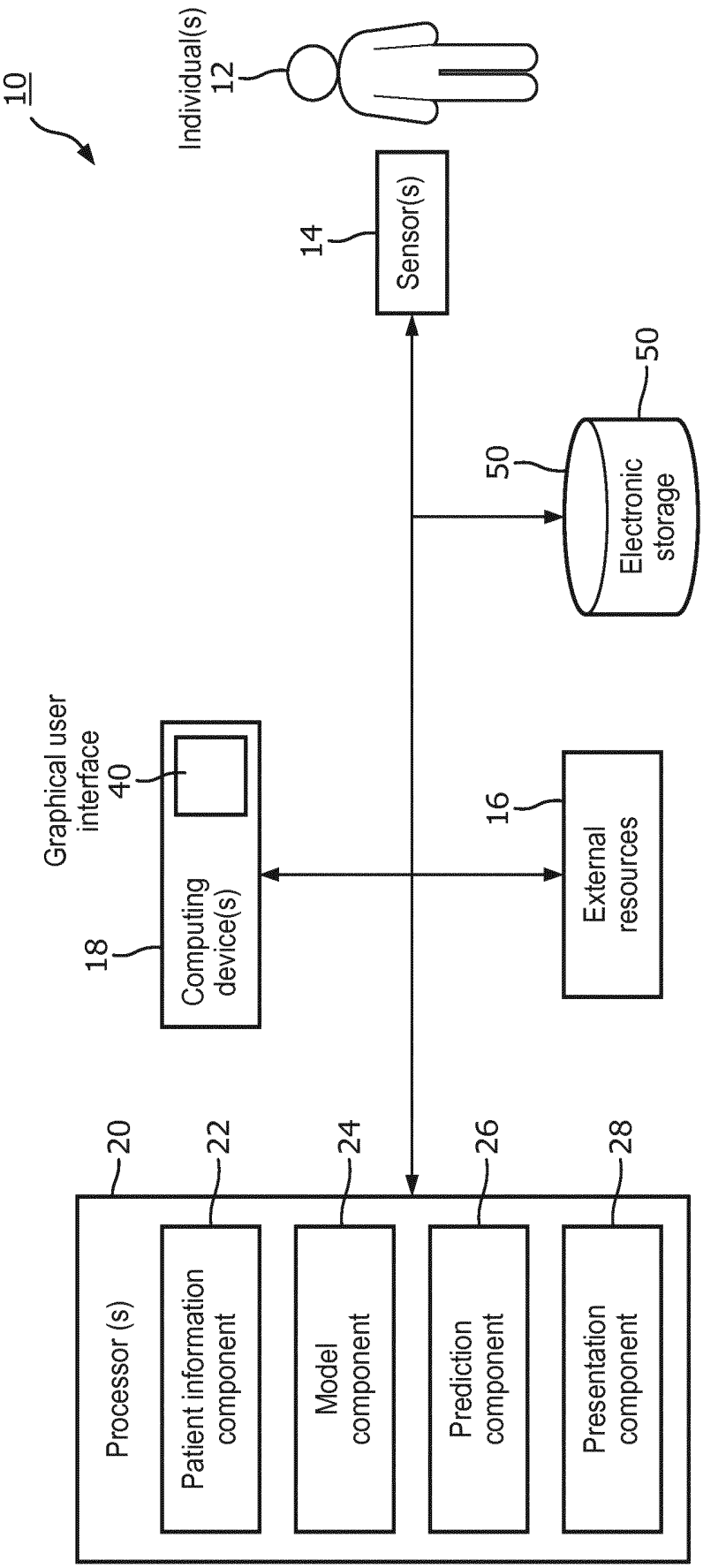

10
Individual(s)
12
14
Sensor(s)
50
50
Electronic storage
Graphical user interface
40
18
Computing device(s)
16
External resources
20
22
24
26
28
Processor (s)
Patient information component
Model component
Prediction component
Presentation component

FIG. 1

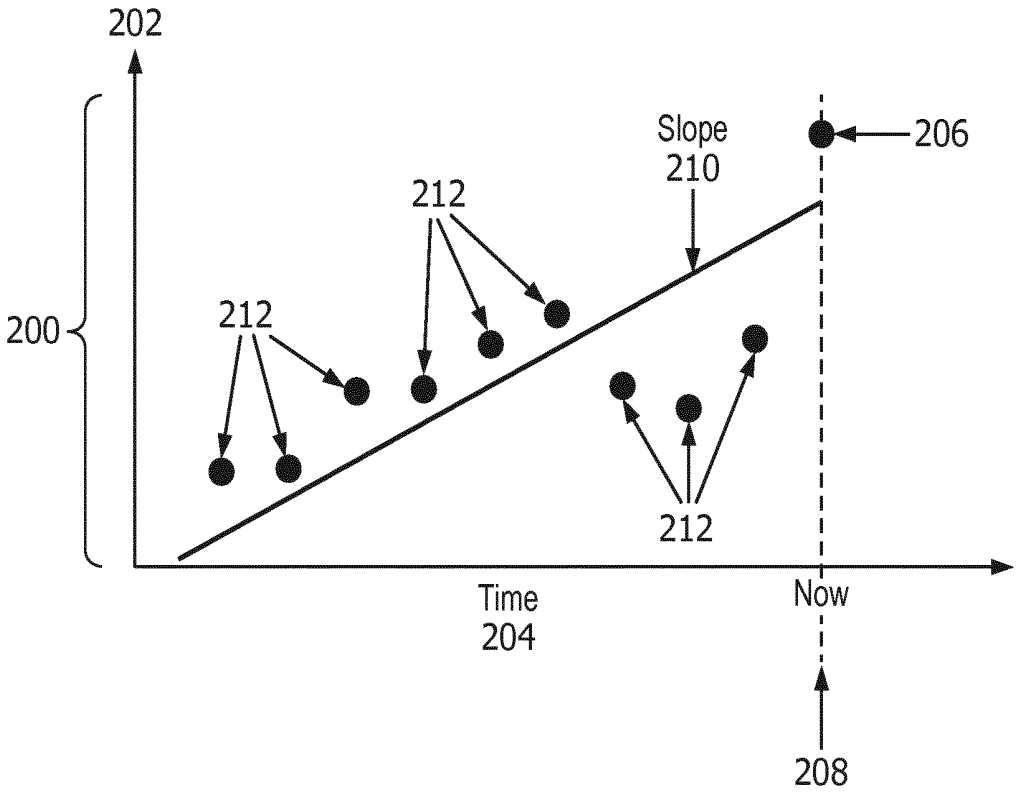

202
200
212
212
Slope
210
206
212
Time
204
Now
208

FIG. 2A

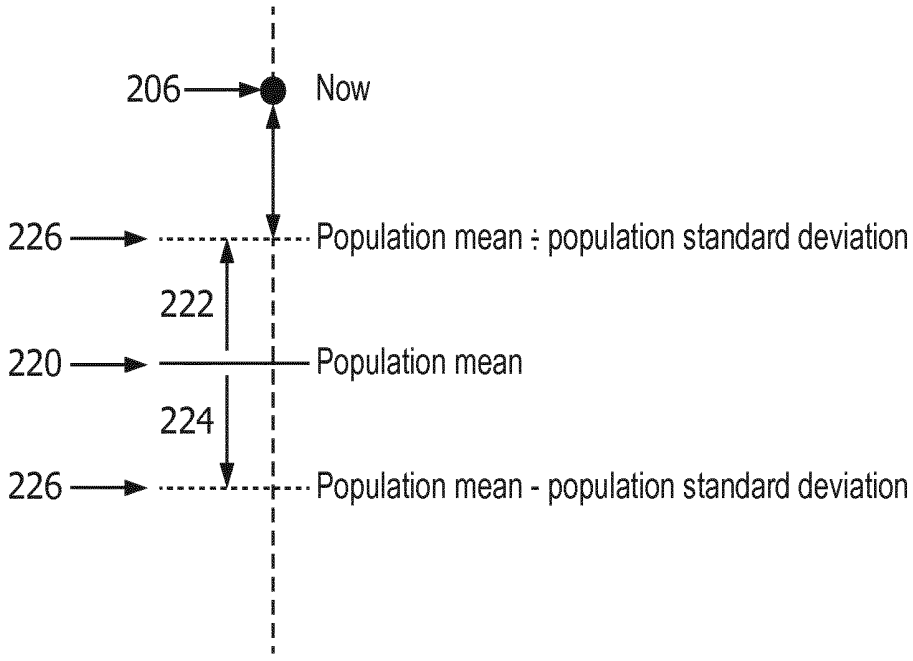

206
Now
226
Population mean + population standard deviation
222
220
Population mean
224
226
Population mean - population standard deviation

FIG. 2B

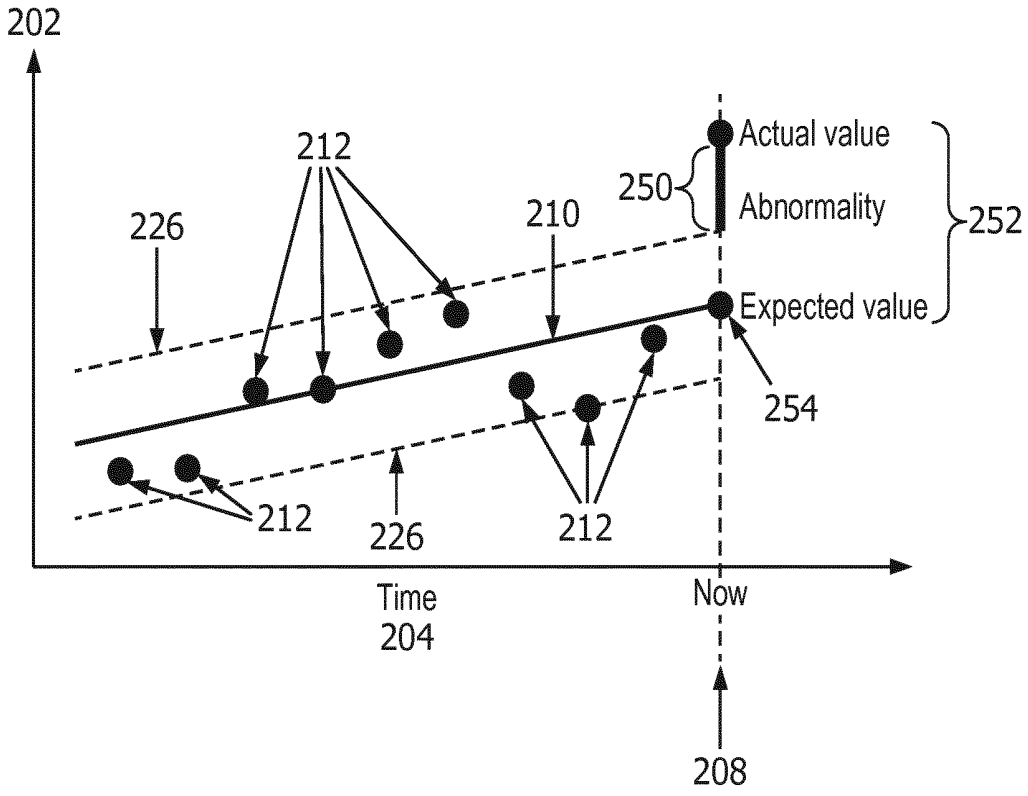

202
212
Actual value
250
Abnormality
252
226
210
Expected value
254
212
226
212
Time
204
Now
208

FIG. 2C

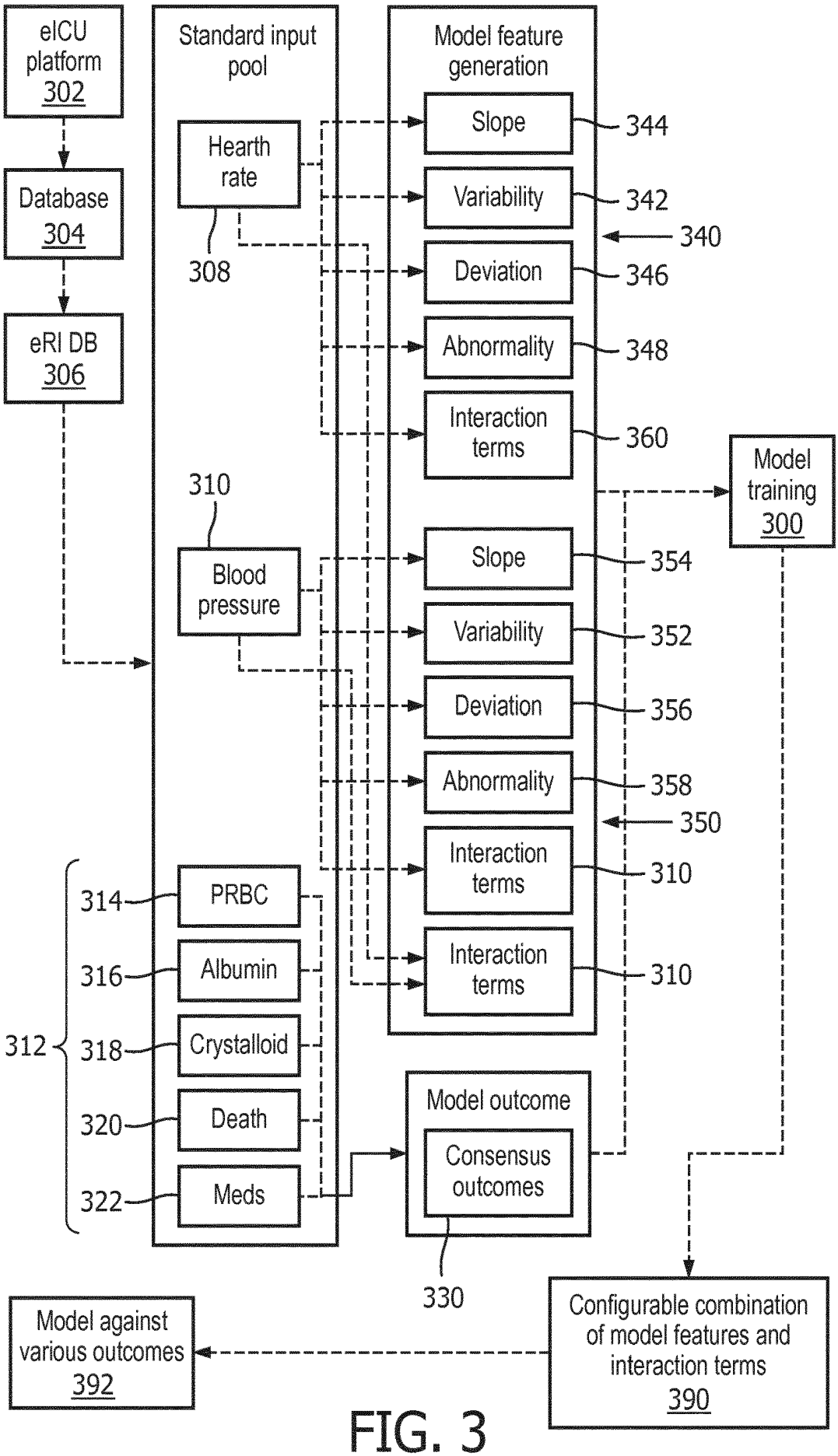

eICU platform 302
Database 304
eRI DB 306
Standard input pool
Hearth rate
308
Blood pressure
310
PRBC
Albumin
Crystalloid
Death
Meds
312
314
316
318
320
322
Model feature generation
Slope
344
Variability
342
340
Deviation
346
Abnormality
348
Interaction terms
360
Slope
354
Variability
352
Deviation
356
Abnormality
358
350
Interaction terms
310
Interaction terms
310
Model training 300
Model outcome
Consensus outcomes
330
Configurable combination of model features and interaction terms 390
Model against various outcomes 392

FIG. 3

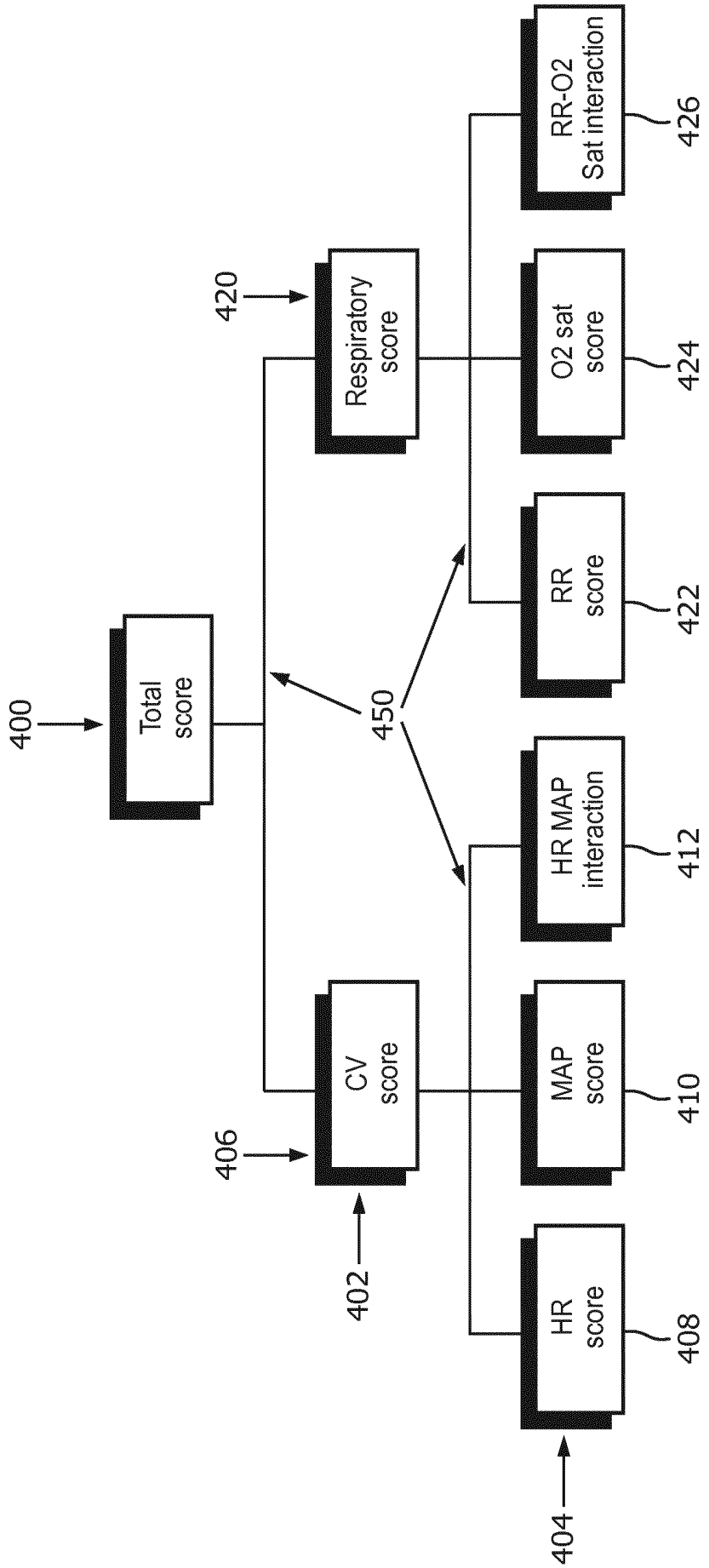

400
Total score
450
420
Respiratory score
406
CV score
402
404
HR score
RR score
O2 sat score
RR-O2 Sat interaction
HR MAP interaction
MAP score
422
424
426
412
410
408

FIG. 4

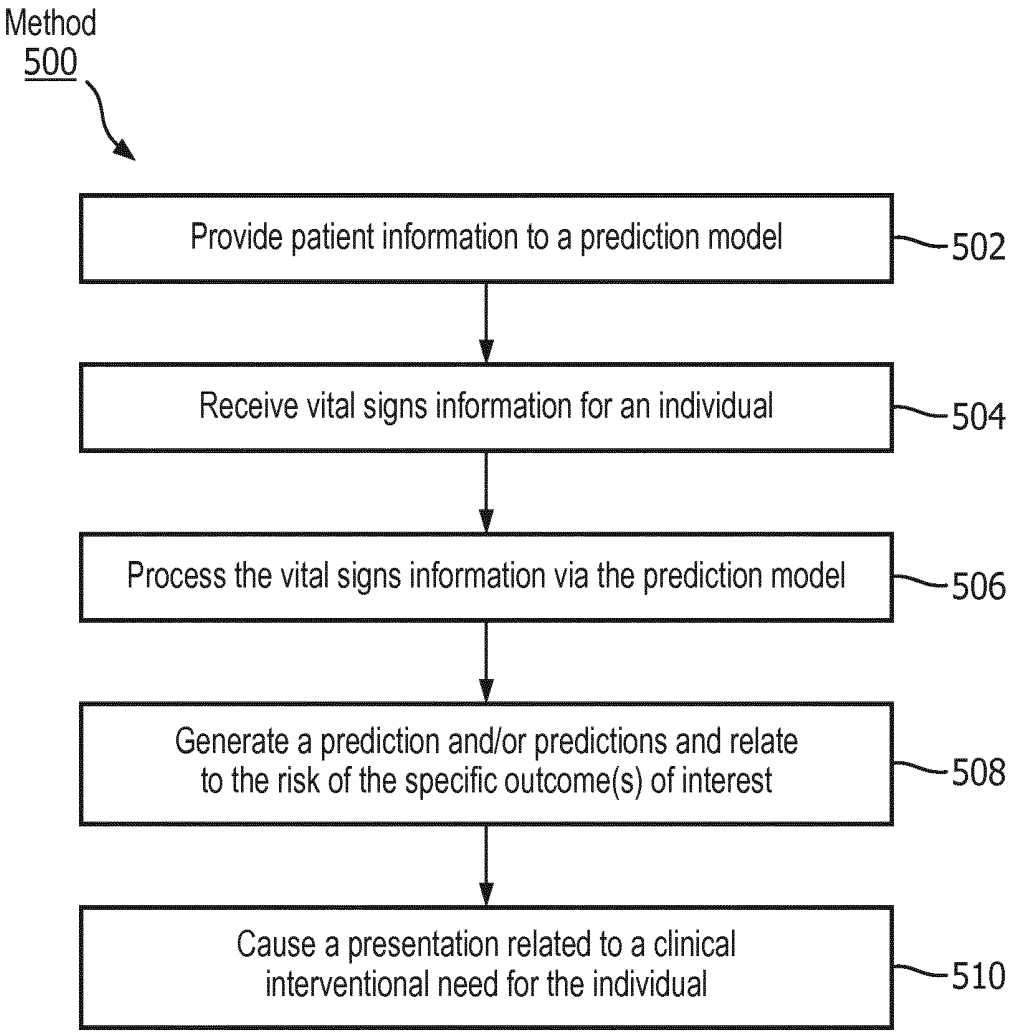

Method
500
Provide patient information to a prediction model
502
Receive vital signs information for an individual
504
Process the vital signs information via the prediction model
506
Generate a prediction and/or predictions and relate to the risk of the specific outcome(s) of interest
508
Cause a presentation related to a clinical interventional need for the individual
510

FIG. 5

SYSTEM AND METHOD FOR PROVIDING A LAYER-BASED PRESENTATION OF A MODEL-GENERATED PATIENT-RELATED PREDICTION

BACKGROUND

1. Field

[0001] The present disclosure pertains to a system and method for presenting a model-generated patient related prediction.

2. Description of the Related Art

[0002] Vital sign threshold-based alert computer systems are known. Typically, such systems generate an alert responsive to the value of a particular monitored vital sign breaching a threshold level, or responsive to the value of the vital sign increasing or decreasing by a predetermined amount over time.

SUMMARY

[0003] Accordingly, one or more aspects of the present disclosure relate to a system configured to provide a layer-based presentation of a model-generated patient-related prediction. The system comprises one or more hardware processors and/or other components. The one or more hardware processors are configured by machine readable instructions to: provide patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients. The training of the prediction model causes the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, diagnosis information, treatment information, patient demographics (e.g., age, gender, etc.), laboratory information, intensive care unit (ICU) and/or hospital characteristics of the ICU and/or hospital treating the patient, and/or other features. The patient information comprises initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments. The processors are further configured to receive, via one or more sensors, vital signs information for one or more vital signs of an individual; process, via the trained prediction model, the vital signs information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features; cause linking of the first prediction and the contributing sub-predictions based on the relatedness information; and cause, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions.

[0004] By way of a non-limiting example, the present system may be configured to gather data retrospectively and train the model offline. Then that model may be deployed and individual patient may receive predictions generated based on applying the model to their patient specific parameters (e.g., vital signs and other parameters). In some embodiments, the present system may be configured such that the model is retrained in real time.

[0005] Another aspect of the present disclosure relates to a method for providing a layer-based presentation of a model-generated patient-related prediction with a prediction system. The system comprises one or more hardware processors configured by machine readable instructions and/or other components. The method comprises: providing patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the training of the prediction model causing the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, diagnosis information, treatment information, patient demographics (e.g., age, gender, etc.), laboratory information, intensive care unit (ICU) and/or hospital characteristics of the ICU and/or hospital treating the patient, and/or other features, the patient information comprising initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments; receiving, via one or more sensors, vital signs information for one or more vital signs of an individual; processing, via the trained prediction model, the vital signs information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features; causing linking of the first prediction and the contributing sub-predictions based on the relatedness information; and causing, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions.

[0006] Still another aspect of present disclosure relates to a system configured to provide a layer-based presentation of a model-generated patient-related prediction. The system comprises: means for providing patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the training of the prediction model causing the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, diagnosis information, treatment information, patient demographics (e.g., age, gender, etc.), laboratory information, intensive care unit (ICU) and/or hospital characteristics of the ICU and/or hospital treating the patient, and/or other features, the patient information comprising initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments; means for receiving, via one or more sensors, vital signs information for one or more vital signs of an individual; means for processing, via the trained prediction model, the vital signs information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii)

relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features; means for causing linking of the first prediction and the contributing sub-predictions based on the relatedness information; and means for causing, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions.

[0007] These and other objects, features, and characteristics of the present disclosure, as well as the methods of operation and functions of the related elements of structure and the combination of parts and economies of manufacture, will become more apparent upon consideration of the following description and the appended claims with reference to the accompanying drawings, all of which form a part of this specification, wherein like reference numerals designate corresponding parts in the various figures. It is to be expressly understood, however, that the drawings are for the purpose of illustration and description only and are not intended as a definition of the limits of the disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] FIG. **1** illustrates a system configured to facilitate patient-related predictions via a prediction model and presentation thereof.

[0009] FIG. **2**A illustrates an amount of variability in a vital sign over time, a value of the vital sign at a given point in time, and a slope of the values of the vital sign over time.

[0010] FIG. **2**B illustrates the value of the vital sign relative to a baseline range for the vital sign, with the default values generated by a historical population mean plus and minus one population standard deviation for the vital sign in a similar population.

[0011] FIG. **2**C illustrates a combination of a prediction for the current vital sign based on prior data, the upper and lower bounds of the confidence interval for the prediction, and an amount the current vital sign value deviates from the expected value of the vital sign.

[0012] FIG. **3** is a schematic illustration of training a predictive model.

[0013] FIG. **4** illustrates a risk score presented to caregivers and/or other users that indicates the probability and or risk of requiring a clinical intervention for an individual.

[0014] FIG. **5** illustrates a method for providing a layer-based presentation of a model-generated patient-related prediction.

DETAILED DESCRIPTION OF EXEMPLARY EMBODIMENTS

[0015] As used herein, the singular form of "a", "an", and "the" include plural references unless the context clearly dictates otherwise. As used herein, the term "or" means "and/or" unless the context clearly dictates otherwise. As used herein, the statement that two or more parts or components are "coupled" shall mean that the parts are joined or operate together either directly or indirectly, i.e., through one or more intermediate parts or components, so long as a link occurs. As used herein, "directly coupled" means that two elements are directly in contact with each other. As used herein, "fixedly coupled" or "fixed" means that two components are coupled so as to move as one while maintaining a constant orientation relative to each other.

[0016] As used herein, the word "unitary" means a component is created as a single piece or unit. That is, a component that includes pieces that are created separately and then coupled together as a unit is not a "unitary" component or body. As employed herein, the statement that two or more parts or components "engage" one another shall mean that the parts exert a force against one another either directly or through one or more intermediate parts or components. As employed herein, the term "number" shall mean one or an integer greater than one (i.e., a plurality).

[0017] Directional phrases used herein, such as, for example and without limitation, top, bottom, left, right, upper, lower, front, back, and derivatives thereof, relate to the orientation of the elements shown in the drawings and are not limiting upon the claims unless expressly recited therein.

[0018] FIG. **1** is a schematic illustration of a system **10** configured to facilitate patient-related predictions via a prediction model and presentation thereof. In some embodiments, system **10** is configured to identify hospitalized patients who are likely to require an intervention and present the information in a form that is clinically meaningful and supports the decision-making process for caregivers (e.g., doctors, nurses, clinicians, family members, friends, etc.). System **10** enables clinicians, for example, and/or other users to efficiently prioritize patients by their probability of need for intervention and easily interpret the rationale for the estimated probability. It should be noted that, although the present disclosure refers to predicting a need for (e.g., acute) intervention in hospitalized (e.g., intensive care unit (ICU)) patients, this is not intended to be limiting. The system and method described herein may apply to any patient-related prediction or other predictions. For example, system **10** may determine the probability of: 1) survival; 2) successful extubation from a ventilator; 3) developing a complication such as acute kidney injury or delirium; and/or other predictions.

[0019] Although computer-assisted patient alert and prediction systems exist, output from such typical systems tends to be difficult to interpret as a user may not be able to intuitively understand how the output was generated. As an example, if a given model-generated risk estimate is generated, it may be difficult for the user to understand how the risk estimate was generated, or why one patient has a higher risk indicator than another patient. In some embodiments, system **10** displays an indication of risk or other prediction that is easy to understand for any given patient or comparison of multiple patients. Additionally, or alternatively, typical systems often define alerting and prediction criteria regardless of individual patient characteristics (e.g., by generating alerts and predictions based on population level data without considering the characteristics of the individual patients) or require manual adjustment of threshold levels for individual patients. In some embodiments, system **10** automatically considers specific vital sign trends for individual patients when determining a patient's risk of needing intervention. In some embodiments, system **10** automatically adjusts threshold levels for individual patients based on the specific vital sign trends of the respective patients or other information.

[0020] In typical systems, criteria for activation of an alert are often arbitrary. For example, if a heart rate alert is set to activate at or above 150 beats per minute (bpm), then this implies a heart rate of 149 bpm is a significantly lower risk than 150 bpm (when in fact the difference in a 149 versus 150 bpm heart rate is very small). Users may be able to modify the threshold in a typical system, but any threshold modification would also be arbitrary. In some embodiments, system **10** overcomes this limitation by determining a risk indicator (e.g., a numeric risk score) which may be used to rank patients on a continuous scale (e.g., which is not arbitrarily cut off at 150 bpm). Additionally, or alternatively, an arbitrary threshold may be used for alerting—however, patients just below the designated threshold will be identifiable, and the relative risk compared to other patients who may be just above the threshold is intuitive to doctors (for example) viewing the displayed indication (e.g., because, as described herein, the risk indicator (a numeric risk score for example) may be a number on a continuous number line, such as 1-100 for example, rather than a red or yellow light, or merely an alarm sound as in prior art systems).

[0021] Typical systems have minimal ability to prioritize one patient over another in a meaningful way. For example, typical systems merely rank patients in order of most recent alert. As another example, in typical systems, any two patients meeting low blood pressure alert criteria will activate similar alerts, even if one patient has a much lower blood pressure than another. Similarly, if one patient also has an abnormal heart rate or respiratory rate, such information would cause an independent alert, which would not be aggregated to raise a treatment risk priority of the patient. Also, typical systems have several different individual alert types (e.g., a heart rate alert, a blood pressure alert, a respiratory rate alert, an oxygen saturation alert, etc.) with multiple subtypes (e.g., trend, threshold, high, low, severe, moderate, etc. as described above). The wide range of physiologic monitoring parameters and alerts can yield a high alarm rate. The high alarm rate may cause alert fatigue (e.g., ignoring alerts, downplaying their importance, etc.) in doctors or nurses (for example) caring for a patient.

[0022] In contrast, in some embodiments, system **10** generates an aggregated output by combining vital signs information for a patient and assigning weights to vital sign feature parameters (described below) appropriately by risk for a given vital sign. For example, a patient with low blood pressure, high heart rate, and high respiratory rate would activate (at least) three different alerts in a typical system. In some embodiments, these vital sign levels would generate a single indication (e.g., a score) which would help a doctor (for example) prioritize the patient over one with a similarly high heart rate but normal blood pressure and respiratory rate.

[0023] As described above, current alert systems may have default threshold values which can be manually tailored for a given patient. This often creates difficulty when sub-populations of patients require the same unique considerations, which would require a user to perform the same manual tailoring for each patient in the sub-population. For example, patients admitted to a mixed ICU after coronary artery bypass grafting (CABG) surgery may have unique physiology that is different than physiology of patients admitted for heart failure. In some embodiments, system **10** is configured such that users can more effectively and efficiently care for these patients because default alert threshold values and/or other system parameters can be managed at a group level, rather than requiring manual customization for individual patients.

[0024] In some embodiments, system **10** is configured to, at a given time, generate a comprehensive indicator (e.g., a score) for monitored patients based on comprehensive vital sign information for a given patient. The indicator represents a need for urgent attention in the patient. In some embodiments, system **10** includes one or more of sensors **14**, external resources **16**, computing devices **18**, processors **20**, electronic storage **50**, and/or other components. It should be noted that a single individual **12** is illustrated in FIG. **1**, but this is not intended to be limiting. System **10** is configured to operate as described herein for any number of individuals **12**.

[0025] Sensors **14** are configured to generate output signals that convey information related to the vital signs and/or other physiological information of individual **12**. In some embodiments, the output signals from sensors **14** are received by processor **20** (described below) and/or other components of system **10**. In some embodiments, sensors **14** include but are not limited to equipment used in hospitals, doctor's offices, and/or other medical facilities to monitor vital signs and/or other physiological information (e.g., pulse rate monitors, blood (e.g., arterial) pressure monitors, blood oxygenation monitors, glucose monitors, respiration monitors, weight scales, thermometers, electrocardiogram (EKG) equipment), test equipment (e.g., imaging equipment such as an MRI and/or an x-ray machine, an ultrasound, electroencephalogram (EEG) equipment, etc.), equipment for treating patients and/or individual(s) **12** (e.g., respirators/ventilators, light therapy devices, etc.), or other devices. In some embodiments, sensors may be included in desktop computers, laptop computers, tablet computers, smartphones, cameras, video equipment, wearable devices, etc., associated with individual(s) **12**, and/or other devices. In some embodiments, sensors **14** include at least one cardiovascular sensor (e.g., a heart rate sensor, a mean arterial pressure sensor, etc.) and at least one respiratory sensor (e.g., a breathing rate sensor). In some embodiments, sensors **14** are operatively coupled to individual **12**. Operative coupling may include any form of removable and/or fixed attachment to individual **12** that facilitates wireless and/or wired transmission of the output signals from sensors **14**. By way of several non-limiting examples, operative coupling may include a blood pressure cuff that is temporarily coupled to the arm of individual **12** using a Velcro strap; a blood oxygen monitor that is clipped to the finger of individual **12**; a respiration sensor that is fixedly coupled to a mask worn by individual **12**; and/or other methods of coupling sensors **14** to individual **12**. In some embodiments, sensors **14** and/or operations performed by sensors **14** may include capturing data by interfacing with a hospital electronic health record (HER) and/or lab system. This could include capturing data related to and/or include patient demographics, diagnosis, treatments, physiology, lab values, and/or other information.

[0026] External resources **16** include sources of patient and/or other information. In some embodiments, external resources **16** include sources of patient and/or other information such as databases, websites, etc.; external entities participating with system **10** (e.g., a medical records system of a health care provider that stores medical history information for populations of patients), one or more servers outside of system **10**, a network (e.g., the internet), elec-

tronic storage, equipment related to Wi-Fi technology, equipment related to Bluetooth® technology, data entry devices, sensors, scanners, and/or other resources. For example, in some embodiments, external resources **16** may include a database where medical history information for a plurality of patients similar to individual **12** and/or other patients are stored, and/or other sources of information such as sources of information related to patient demographics, diagnoses, problem lists, treatments, lab data, and/or other information. In some embodiments, the patient information comprises initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, respective vital signs resulting from the treatments, and/or other information. In some implementations, some or all of the functionality attributed herein to external resources **16** may be provided by resources included in system **10**. External resources **16** may be configured to communicate with processor **20**, computing devices **18**, sensors **14**, electronic storage **50**, and/or other components of system **10** via wired and/or wireless connections, via a network (e.g., a local area network and/or the internet), via cellular technology, via Wi-Fi technology, and/or via other resources.

[0027] Computing devices **18** are configured to provide interfaces between caregivers (e.g., doctors, nurses, friends, family members, etc.), individual **12**, and/or other users, and system **10**. In some embodiments, individual computing devices **18** are and/or are included in desktop computers, laptop computers, tablet computers, smartphones, and/or other computing devices associated with individual caregivers, individual **12**, and/or other users. In some embodiments, individual computing devices **18** are, and/or are included in equipment used in hospitals, doctor's offices, and/or other medical facilities to monitor individual **12**; test equipment; equipment for treating individual **12**; data entry equipment; and/or other devices. Computing devices **18** are configured to provide information to and/or receive information from the caregivers, individual **12**, and/or other users. For example, computing devices **18** are configured to present a graphical user interface **40** to the caregivers to facilitate display of a risk score and/or other information for individual **12** (e.g., as described below). In some embodiments, graphical user interface **40** includes a plurality of separate interfaces associated with computing devices **18**, processor **20** and/or other components of system **10**; multiple views and/or fields configured to convey information to and/or receive information from caregivers, individual **12**, and/or other users; and/or other interfaces.

[0028] In some embodiments, computing devices **18** are configured to provide graphical user interface **40**, processing capabilities, databases, and/or electronic storage to system **10**. As such, computing devices **18** may include processors **20**, electronic storage **50**, external resources **16**, sensors **14**, and/or other components of system **10**. In some embodiments, computing devices **18** are connected to a network (e.g., the internet). In some embodiments, computing devices **18** do not include processors **20**, electronic storage **50**, external resources **16**, sensors **14**, and/or other components of system **10**, but instead communicate with these components via the network. The connection to the network may be wireless or wired. For example, processor **20** may be located in a remote server and may wirelessly cause display of graphical user interface **40** to the caregivers on computing devices **18**. As described above, in some embodiments, an individual computing device **18** is a laptop, a personal computer, a smartphone, a tablet computer, and/or other computing devices. Examples of interface devices suitable for inclusion in an individual computing device **18** include a touch screen, a keypad, touch sensitive and/or physical buttons, switches, a keyboard, knobs, levers, a display, speakers, a microphone, an indicator light, an audible alarm, a printer, and/or other interface devices. The present disclosure also contemplates that an individual computing device **18** includes a removable storage interface. In this example, information may be loaded into a computing device **18** from removable storage (e.g., a smart card, a flash drive, a removable disk) that enables the caregivers, individual **12**, and/or other users to customize the implementation of computing devices **18**. Other exemplary input devices and techniques adapted for use with computing devices **18** include, but are not limited to, an RS-232 port, RF link, an IR link, a modem (telephone, cable, etc.) and/or other devices.

[0029] Processor **20** is configured to provide information processing capabilities in system **10**. As such, processor **20** may comprise one or more of a digital processor, an analog processor, a digital circuit designed to process information, an analog circuit designed to process information, a state machine, and/or other mechanisms for electronically processing information. Although processor **20** is shown in FIG. **1** as a single entity, this is for illustrative purposes only. In some embodiments, processor **20** may comprise a plurality of processing units. These processing units may be physically located within the same device (e.g., a server), or processor **20** may represent processing functionality of a plurality of devices operating in coordination (e.g., one or more servers, one or more computing devices **18** associated with caregivers, a piece of hospital equipment, sensors **14**, devices that are part of external resources **16**, electronic storage **50**, and/or other devices.)

[0030] In some embodiments, processor **20**, sensors **14**, external resources **16**, computing devices **18**, electronic storage **50**, and/or other components may be operatively linked via one or more electronic communication links. For example, such electronic communication links may be established, at least in part, via a network such as the Internet, and/or other networks. It will be appreciated that this is not intended to be limiting, and that the scope of this disclosure includes embodiments in which these components may be operatively linked via some other communication media. In some embodiments, processor **20** is configured to communicate with sensors **14**, external resources **16**, computing devices **18**, electronic storage **50**, and/or other components according to a client/server architecture, a peer-to-peer architecture, and/or other architectures.

[0031] As shown in FIG. **1**, processor **20** is configured via machine-readable instructions to execute one or more computer program components. The one or more computer program components may comprise one or more of a patient information component **22**, a model component **24**, a prediction component **26**, a presentation component **28**, and/or other components. Processor **20** may be configured to execute components **22**, **24**, **26**, and/or **28** by software; hardware; firmware; some combination of software, hardware, and/or firmware; and/or other mechanisms for configuring processing capabilities on processor **20**.

[0032] It should be appreciated that although components **22**, **24**, **26**, and **28** are illustrated in FIG. **1** as being co-located within a single processing unit, in embodiments

in which processor **20** comprises multiple processing units, one or more of components **22**, **24**, **26**, and/or **28** may be located remotely from the other components. The description of the functionality provided by the different components **22**, **24**, **26**, and/or **28** described below is for illustrative purposes, and is not intended to be limiting, as any of components **22**, **24**, **26**, and/or **28** may provide more or less functionality than is described. For example, one or more of components **22**, **24**, **26**, and/or **28** may be eliminated, and some or all of its functionality may be provided by other components **22**, **24**, **26**, and/or **28**. As another example, processor **20** may be configured to execute one or more additional components that may perform some or all of the functionality attributed below to one of components **22**, **24**, **26**, and/or **28**.

[0033] In some embodiments, patient information component **22** is configured to obtain patient information. The patient information indicates health information for a plurality of patients and/or other information. The health information may be related to vital signs of the plurality of patients, physical conditions experienced by the plurality of patients, medical records describing previous medical treatment provided to the plurality of patients, and/or other information. For example, the patient information may comprise initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, respective vital signs resulting from the treatments, and/or other information.

[0034] Patient information component **22** is configured to obtain the patient information from external resources **16** (e.g., one or more external databases included in external resources **16**), electronic storage **50** included in system **10**, one or more sensors **14**, and/or other sources of information. For example, the patient information may be obtained from an electronic ICU (eICU) platform and/or other sources.

[0035] In some embodiments, an eICU platform is a telehealth software application, designed to provide clinicians with a set of tools that display organized clinical information and highlight interrelationships. Used by an integrated team of bedside and remote clinicians, the system helps facilitate the delivery of high quality in-hospital care and supports rapid recognition of potential patient problems. This comprehensive view of a patients' clinical status supports timely decision-making and effective communication and coordination among the care team, while helping to plan, document and standardize care around best practices.

[0036] In some embodiments, the patient information is anonymized (e.g., processed to remove any information that might identify a particular patient) by patient information component **22** and stored in a relational database (e.g., such as an electronic research institute (eRI) database) and/or other databases. In some embodiments, patient information component **22** is configured to perform natural language processing on the patient information, and generate variable files for vital signs (such as heart rate, blood pressure, etc.) and clinically relevant (to the particular treatment received by a given patient) interventions and/or events (e.g., such as blood infusions, albumin usage, provision of a fluid bolus, vasoactive usage, death, etc.). In some embodiments, patient information component **22** uses a sliding window technique to scan heart rate (HR), mean arterial pressure (MAP), and/or other vital sign information (these two examples are not intended to be limiting) through 60 minute, 180 minute, and/or other windows of time for a duration of a patient's stay in a medical facility, respectively. The 60 minute and 180 minute durations described above are only examples and are not intended to be limiting. Other windows of time may be used. In some embodiments, patient information component **22** is configured to combine and/or correlate the information from the clinically relevant interventions and/or events with the vital signs from the corresponding windows of time and generate consensus categorical outcome determinations (e.g., whether the patient was stable, unstable, status unable to be determined, etc.). In some embodiments, these features (vital signs, clinically relevant interventions and/or events) and outcomes (stable, unstable, unknown) comprise input for a prediction model (described below).

[0037] In some embodiments, model component **24** is configured to provide the patient information to the prediction model. As described above, the patient information comprises information related to initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, respective vital signs resulting from the treatments (e.g., the features (vital signs, clinically relevant interventions and/or events) and outcomes (stable, unstable, unknown)), and/or other information. In some embodiments, the prediction model is a logistic regression model and/or other models. The patient information is provided to the prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients and/or for other purposes. In some embodiments, model component **24** is configured such that the logistical regression model (or other statistical model) is trained and validated using cross-validation and/or other techniques. In some embodiments, model component **24** is configured such that the predictive model is designed with a set of features specifically used due to their clinically relevant distinctions. For example, a decreasing blood pressure will likely indicate a higher risk for need of fluid resuscitation if the patient has a low blood pressure, rather than a high blood pressure. The predictive model is designed to account for these clinically meaningful groups by creating unique coefficients for a wide variety of clinical combinations. In some embodiments, system **10** is designed to be configurable so new groups and/or new weights can be introduced as models evolve.

[0038] In some embodiments, the training and/or validation of the prediction model causes the prediction model to develop weighted predictive parameter features that correspond to patient vital signs and/or other patient information. For example, model component **24** is configured such that weighted predictive parameter features corresponding to vital signs, trends in vital signs, particular medical facilities (e.g., different types of ICU's), types of patients (e.g., a heart failure patient versus a CABG patient), and/or other patient information are determined. In some embodiments, model component **24** may be configured such that a given predictive parameter feature is a combination of two or more other weighted predictive parameter features.

[0039] In some embodiments, model component **24** is configured such that individual weights (e.g., coefficients) are determined for individual predictive parameter features. In some embodiments, the individual weights are determined based on a type of patient information associated with the predictive parameter features and/or other information. Continuing with the example above, different weights may be determined for predictive parameter features corresponding to different vital signs and/or trends in vital signs,

different weights may be determined for predictive parameter features corresponding to particular medical facilities (e.g., different types of ICU's), different weights may be determined for predictive parameter features corresponding to different types of patients (e.g., a heart failure patient versus a CABG patient), and/or other weighting may be determined. In some embodiments, model component **24** is configured such that individual weights are manually entered and/or selected (e.g., via a computing device **18**) by caregivers and/or other users.

[0040] In some embodiments, model component **24** is configured such that the weighted parameters are developed by training a model to identify near term interventions in patients and identify the weights for parameters predictive of these outcomes. Similar outcomes are grouped together (e.g., bolus of fluids and initiation of vasopressors) to create a model which can complement other models targeting other outcomes such as need for intubation or ventilator support. The clinical relevance of the groupings allow for different weights to be derived in meaningful ways which will be intuitive for clinicians.

[0041] By way of a non-limiting example, in some embodiments, the weighted predictive parameter features include an amount of variability in a given vital sign, a slope for the given vital sign determined based on values of the given vital sign over time, an amount of deviation from a baseline value and/or range (e.g., baseline heart rate is between about 70 and about 90 beats per minute) baseline range for the given vital sign, an amount of deviation from an expected level of the given vital sign for the monitored individual, and/or other features. In some embodiments, system **10** may be configured such that individual patients have a baseline value for a vital sign and/or some other parameter, but the system is configured to default the algorithm to using a population derived value (e.g., as described herein). In some embodiments, system **10** may be configured such that users are able to modify and/or adapt a patient specific baseline as well as the baseline for sub-populations of their choice (e.g., all heart failure patients, all male heart failure patients above 65 years of age, etc.). In some embodiments, system **10** may determine a patient specific baseline based on available previously recorded data.

[0042] As an example, at least one of the predictive parameter features may be a combination of the slope for the given and the amount of deviation from the baseline range for the given sign, a combination of the amount of deviation from the baseline range for the given vital sign and the amount of deviation from the expected level of the given vital sign for the monitored individual, other combinations, or a feature generated from one or more of the foregoing combinations. Example weighted predictive parameter features are illustrated in FIG. **2**A-FIG. **2**C. FIG. **2**A illustrates an amount of variability **200** in a vital sign **202** over time **204**, a value **206** of vital sign **202** at a given point **208** in time ("now"), and a slope **210** of the values **212** of vital sign **202** over time **204**. FIG. **2**B illustrates value **206** of vital sign **202** (FIG. **2**A) relative to a baseline range **220** for vital sign **202**, and relative to baseline range **220** plus **222** and minus **224** one population standard deviation (used as an example only and is not intended to be limiting) **226** for vital sign **202**. Baseline range **220** and/or population standard deviations **226** may be for the population of patients whose patient data was obtained by patient information component **22** described above related to FIG. **1**, and/or other populations. FIG. **2**C illustrates a combination of slope **210** for vital sign **202**, an amount of deviation **250** from baseline range **220** plus one standard deviation **226** for vital sign **202**, and an amount of deviation **252** from an expected level **254** of vital sign **202**.

[0043] FIG. **3** is a schematic illustration of training **300** the predictive model using patient information (including the vital signs and clinically relevant interventions and/or events), weighed predictive parameter features described above, interaction terms, or other information. In some embodiments, interaction terms include the ability to stratify weights by clinically meaningful groups. For example, if there are five defined categories of blood pressure deviation from baseline and five categories for the trend/slope of the patient's blood pressure, then there would be 25 possible unique combinations when these parameters are 'interacted' in a regression model. In this scenario, each unique combination will receive a unique weight relative to the risk associated with a patient being in that group. Furthermore, these interaction terms can continue to expand as is clinically useful and is supported by available data. For example, the above example can also be interacted with unique combinations of five (or other numbers) categories of heart rate trends/slope. Addition of this interaction term would create 125 possible unique combinations of heart rate slope, blood pressure deviation from baseline and blood pressure slope. Each of these will create highly specific weights for patients falling into these categories and thereby increase the clinical accuracy, relevance, and interpretation of the model output.

[0044] For example, as shown in FIG. **3**, patient information may be obtained from an eICU platform **302** and stored in a database **304**. The patient information may be anonymized and stored in a relational database **306**. In some embodiments, the patient information is processed using natural language processing to generate variable files for vital signs (such as heart rate **308**, blood pressure **310**, etc.) and clinically relevant interventions and/or events **312** (e.g., such as packed red blood cell (PRBC) infusion **314**, albumin usage **316**, crystalloid **318**, death **320**, provision of medication **322**, etc.). In some embodiments, the information from the clinically relevant interventions and/or events are combined and/or correlated with the vital signs from the corresponding windows of time to generate consensus categorical outcome determinations **330**. The prediction model may develop and/or validate (e.g., after training) weighted predictive parameter features **340** (e.g., corresponding to a first vital sign and/or other characteristics of a patient) and **350** (e.g., corresponding to a second vital sign and/or other characteristics of a patient), interaction terms **360** (e.g., corresponding to the first vital sign type and/or other characteristics) and **370** (e.g., corresponding to the second vital sign type and/or other characteristics), and/or other information that correspond to patient vital sign types (the example of two different sets of features is not intended to be limiting). As shown in FIG. **3**, there may be more than one interaction term and/or set of interaction terms **370** that correspond to a given vital sign type. As described above, in some embodiments, the weighted predictive parameter features include an amount of variability in a given vital sign **342** and **352**, a slope for the given vital sign **344** and **354**, a combination of the slope for the given vital sign and an amount of deviation from a baseline range for the given vital sign **346** and **356**, and an amount of deviation from an

expected level of the given vital sign **348** and **358** (these examples are not intended to be limiting). Finally, a configurable combination of model features and interaction terms **390** (e.g., configured by entry and/or selection by a user) may be used by the trained model to predict various outcomes **392**. Example 1 below describes an example trained logistical regression model that uses heart rate and mean arterial blood pressure to predict cardio vascular (CV) intervention or death.

[0045] Returning to FIG. **1**, in some embodiments, model component **24** is and/or includes a population level configuration component and a patient level configuration component. The population level configuration may allow users to flexibly configure the weights, thresholds, default values, and/or other information for sub-populations at a time. For example, a user may increase the default alerting threshold for the entire cardiac surgery unit. As another example, the population level configuration component may facilitate changing the default baseline blood pressure values for heart failure patients admitted to the medical ICU. As a further example, the patient level configuration component may allow for specific adaptation of the system parameters for a given patient.

[0046] In some embodiments, prediction component **26** is configured to receive the vital signs information for individual **12** and/or other individuals. Prediction component **26** is configured to receive the vital signs information from sensors **14** and/or other devices. Prediction component **26** is configured to process the vital signs information via the prediction model (e.g., by providing the vital signs information as input to the prediction model to cause the prediction model to process the vital signs information and generate one or more outputs based thereon). In some embodiments, the processing, via the prediction model, generates (i) a first prediction related to a clinical intervention need for the individual **12** (e.g., a risk score or other prediction), (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related. The contributing sub-predictions correspond to respective ones of the weighted predictive parameter features and/or other information. In some embodiments, the processing of the vital signs information includes causing linking of the first prediction and the contributing sub-predictions based on the relatedness information and/or other information. As an example, by generating the predictions for different outcomes, the aggregate risk can be used. For example, a patient may have a high risk for intubation and a moderate risk for cardiovascular resuscitation. Together, this patient would have higher overall risk than a patient who only has a high risk for intubation but low risk for cardiovascular resuscitation.

[0047] In some embodiments, presentation component **28** is configured to cause a presentation related to a clinical intervention need for individual **12**. The presentation is caused to be provided on user interface **40** and/or other user interfaces based on the first prediction related to a clinical intervention need for the individual, the sub-predictions contributing to the first prediction or to at least another one of the sub-predictions, the relatedness information indicating how the first prediction and the contributing sub-predictions are related, the linking information (e.g., as described above), and/or other information. In some embodiments, the presentation comprises graphical or other representations of the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions. As an example, when a user taps, clicks, holds, releases, hoover over, etc., a representation of the first prediction, one or more of the contributing sub-predictions may be displayed on the user interface (e.g., in lieu of the first prediction, along with the first prediction, etc.). In some embodiments, the prediction model (described above) comprises a cardiovascular prediction model, a respiratory prediction model, and/or other models. In such embodiments, the presentation related to the clinical intervention need for the individual is a combination of a cardiovascular indicator determined based on weighted predictive cardiovascular parameter features and a respiratory indicator determined based on weighted predictive respiratory parameter features. In some embodiments, presentation component **28** is configured such that the presentation related to a clinical intervention need for individual **12** is a presentation of a risk score or other information. The risk score may be indicative of a need for acute intervention and/or other information.

[0048] By way of a non-limiting example, FIG. **4** illustrates a risk score **400** presented to caregivers and/or other users that indicates a clinical intervention need for individual **12** (FIG. **1**). FIG. **4** illustrates a layer-based presentation, but this is not intended to be limiting. In the example shown in FIG. **4**, the presentation (e.g., risk score **400** comprises the first prediction (risk score **400**) in a first layer and the contributing sub-predictions **402** and **404** in second and third layers (the illustration of three layers is not intended to be limiting). In the example shown in FIG. **4**, the prediction model (described above) comprises a cardiovascular prediction model, and a respiratory prediction model. In this example, the presentation related to the clinical intervention need for the individual (risk score **400**) is a combination of a cardiovascular (CV) indicator (score) **406** determined based on weighted predictive cardiovascular parameter features (heart rate (HR) score **408**, mean arterial pressure (MAP) score **410**, HR-MAP interaction **412**) and a respiratory indicator (score) **420** determined based on weighted predictive respiratory parameter features (respiratory rate (RR) score **422**, oxygen (O2) saturation (Sat) score **424**, RR-O2 Sat interaction score **426**). As shown in FIG. **4**, the relatedness information indicating how the first prediction (risk score **400**) and the contributing sub-predictions (**406**-**426**) and the linking between such contributors to the overall score are illustrated by connecting lines **450**.

[0049] In some embodiments, individual **12** (FIG. **1**) comprises a plurality of individuals (as described above), and presentation component **28** (FIG. **1**) is configured to cause display of risk scores for the plurality of individuals. In some embodiments, presentation component **28** is configured to generate an ordered display representative of the plurality of individuals based on risk scores associated with the plurality of individuals. In such embodiments, presentation component **28** may be configured such that individuals **12** are ranked by the total score produced from the model (e.g., risk score **400**), but presentation component **28** facilitates easy visualization of the second (**402**), third (**406**), and even fourth (not shown) layers of features contributing to risk. The fourth layer may be comprised, for example, of the core model which describes how individual scores (e.g., HR Score **408**) was calculated in a clinically meaningful way.

By way of a non-limiting example, Example 2 below shows example calculations and/or categorization of HR Score **408** and MAP Score **410**, deviation from baseline (e.g., as shown in FIG. **2**B), and deviation from (e.g., linear—this is not intended to be limiting—and/or other) projection covariates (e.g., as shown in FIG. **2**C) using a predictive model for a given patient. The system allows for a large number of unique categories. If each of the 6 example parameters are classified into 5 categories and modeled independently, there would be 30 coefficients/weights. If two of these terms are interacted, there would be 45 coefficients (5×5=25 plus the other 4 parameters of 5 categories each). If three terms are interacted, there would be 140 coefficients (125 plus 15). If all 6 terms are interacted, there would be 15,625 unique combinations.

[0050] In some embodiments, presentation component **28** is configured such that user selection related to the first prediction (risk score **400**) causes display of one or more of the contributing sub-predictions (e.g., the scores in layers **402**, **404**). For example, initially, only risk score **400** may be displayed by presentation component **28** on a touch screen of a computing device **18** (FIG. **1**). Responsive to a caregiver and/or other users touching risk score **400** on the touch screen, presentation component **28** may cause the display to expand to show layer **402**. Responsive to a similar touch on one of the sub-predictions in layer **402** (e.g., scores **406** and/or **420**), presentation component may cause the display to expand to show layer **404**, and so on.

[0051] Presentation component **28** is configured to expand the display to shown one or more given sub-predictions based on the relatedness information and/or the linking determined by prediction component **26** (FIG. **1**) and/or other information. For example, in this example, prediction component **26** determined that HR score **408**, MAP score **410**, and HR-MAP interaction **412** are related to, and should be linked with, CV score **406**. Scores **406**, **422**, **424**, and **426** are also similarly related and linked.

[0052] In some embodiments, presentation component **28** is configured such that users can change the baseline values and/or weights for a given patient. For example, if a patient is known to have a high baseline heart rate due to an arrhythmia, the user can increase the baseline range for heart rate for that patient. This would decrease estimated risk for the patient with a high heart rate for the general population but relatively normal for this patient. In some embodiments, presentation component **28** may be configured such that users can change the threshold to alert for a given patient. This would allow users to acknowledge a patient has high risk but may not want to be notified unless their risk increases to a certain level.

[0053] Presentation component **28** is configured such that a user may similarly collapse the display back to risk score **400**. In some embodiments, presentation component **28** is configured such that expanding display layers does not require user selection. For example, presentation component **28** may be configured such that the touch screen automatically displays risk score **400** (the first prediction) initially and then automatically displays layers **402** and **404** (the contributing sub-predictions) over time (e.g., based on their hierarchy and/or how they contribute to the first prediction), and/or for other reasons.

[0054] Using these clinically interpretable scores (for example), caregivers may easily understand why an individual **12** (FIG. **1**) has a particular risk score and why the risk of the individual is higher or lower than another individual **12**. In addition, system **10** (FIG. **1**) may be configured to recalibrate a given model for different subgroups of patients to enhance an accuracy and/or meaningfulness of scores (described below). For example, a set of coefficients (weights) and/or population average values may differ for CABG patients than for patients admitted with heart failure. As such, the probability of needing an acute intervention may differ for two patients of these two different clinical subtypes (e.g., CABG patients versus heart failure patients). These subtypes may vary based on more than just admission diagnosis. Other subtypes may be based on age, ICU type, length of stay, etc., as well as combinations of subtypes (e.g., older heart failure patients versus younger heart failure patients, etc.).

[0055] Again, it should be emphasized that FIG. **4** is one example of many possible examples, and it is not intended to be limiting. For example, FIG. **4** could have been drawn to be more generic to represent the HR and MAP values along with other parameters yet to be determined.

[0056] Returning to FIG. **1**, in some embodiments, model component **24**, prediction component **26**, presentation component **28**, and/or other components of processor **20** and/or system **10** are configured to continuously provide additional patient information as input to the prediction model to further train the prediction model for generating predictions related to a need for clinical intervention for individual patients (e.g., by periodically providing the additional patient information, by automatically providing the additional patient information as it become available, or via other continuous techniques). The further training of the prediction model may cause the prediction model to develop an updated set of weighted predictive parameter features, for example. The updated set may be developed by one or more of (i) modification of the weighted predictive parameter features, (ii) removal of at least one of the weighted predictive parameter features from the prediction model, (iii) development of one or more additional weighted predictive parameter features, (iv) modifying interaction terms and/or categories, and/or other operations. In some embodiments, for example, prediction component **26** is configured to continuously receive, via one or more sensors **14**, additional vital signs information for the one or more vital signs of individual **12** (e.g., by periodically obtaining the additional vital signs information, automatically obtaining the additional vital signs information as it become available, or via other continuous techniques). Prediction component **26** is configured to process, via the further-trained prediction model, the additional vital signs information to generate (i) an additional prediction related to a clinical intervention need for the individual, (ii) additional sub-predictions contributing to the additional prediction or to at least another one of the additional sub-predictions, (iii) additional relatedness information indicating how the additional prediction and the contributing additional sub-predictions are related, and/or other information. The contributing additional sub-predictions correspond to respective ones of the weighted predictive parameter features of the updated set. In some embodiments, model component **24**, prediction component **26**, presentation component **28**, and/or other components are configured to cause linking of the additional prediction and the contributing additional sub-predictions based on the additional relatedness information; and update the information displayed on user interface **40** and/or other interfaces,

based on the linking of the additional prediction and the contributing additional sub-predictions. The updated prediction (e.g., score) comprises the additional prediction and the additional contributing sub-predictions such that user selection related to the additional prediction causes display of one or more of the contributing additional sub-predictions.

[0057] Electronic storage **50** comprises electronic storage media that electronically stores information. The electronic storage media of electronic storage **50** may comprise one or both of system storage that is provided integrally (i.e., substantially non-removable) with system **10** and/or removable storage that is removably connectable to system **10** via, for example, a port (e.g., a USB port, a firewire port, etc.) or a drive (e.g., a disk drive, etc.). Electronic storage **50** may be (in whole or in part) a separate component within system **10**, or electronic storage **50** may be provided (in whole or in part) integrally with one or more other components of system **10** (e.g., computing devices **18**, processor **20**, etc.). In some embodiments, electronic storage **50** may be located in a server together with processor **20**, in a server that is part of external resources **16**, in a computing device **18**, and/or in other locations. Electronic storage **50** may comprise one or more of optically readable storage media (e.g., optical disks, etc.), magnetically readable storage media (e.g., magnetic tape, magnetic hard drive, floppy drive, etc.), electrical charge-based storage media (e.g., EPROM, RAM, etc.), solid-state storage media (e.g., flash drive, etc.), and/or other electronically readable storage media. Electronic storage **50** may store software algorithms, information determined by processor **20**, information received via a computing device **18** and/or graphical user interface **40** and/or other external computing systems, information received from external resources **16**, information received from sensors **14**, and/or other information that enables system **10** to function as described herein.

[0058] FIG. **5** illustrates a method **500** for providing a layer-based presentation of a model-generated patient-related prediction with a prediction system. The system comprises one or more hardware processors and/or other components. The one or more hardware processors are configured by machine readable instructions to execute computer program components. The computer program components include a patient information component, a model component, a prediction component, a presentation component, and/or other components. The operations of method **500** presented below are intended to be illustrative. In some embodiments, method **500** may be accomplished with one or more additional operations not described, and/or without one or more of the operations discussed. Additionally, the order in which the operations of method **500** are illustrated in FIG. **5** and described below is not intended to be limiting.

[0059] In some embodiments, method **500** may be implemented in one or more processing devices (e.g., a digital processor, an analog processor, a digital circuit designed to process information, an analog circuit designed to process information, a state machine, and/or other mechanisms for electronically processing information). The one or more processing devices may include one or more devices executing some or all of the operations of method **500** in response to instructions stored electronically on an electronic storage medium. The one or more processing devices may include one or more devices configured through hardware, firmware, and/or software to be specifically designed for execution of one or more of the operations of method **500**.

[0060] At an operation **502**, patient information is provided to a prediction model. The patient information is provided to the prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients and/or for other purposes. The training of the prediction model causes the prediction model to develop weighted predictive parameter features that correspond to patient vital signs and/or other parameters. In some embodiments, the weighted predictive parameter features include an amount of variability in a given vital sign, a slope for the given vital sign determined based on values of the given vital sign over time, a combination of the slope for the given vital sign and an amount of deviation from a baseline range for the given vital sign, a combination of an amount of deviation from an expected level of the given vital sign for the monitored individual, and the amount of deviation from the baseline range for the given vital sign, and/or other features. The patient information comprises initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, respective vital signs resulting from the treatments, and/or other information. In some embodiments, operation **502** is performed by a processor component the same as or similar to patient information component **22** and/or model component **24** (shown in FIG. **1** and described herein).

[0061] At an operation **504**, vital signs information for an individual is received. In some embodiments, the vital signs information is received from one or more sensors operatively coupled to the individual. In some embodiments, the one or more sensors include at least one cardiovascular sensor and one respiratory sensor. In some embodiments, operation **504** is performed by a processor component the same as or similar to prediction component **26** (shown in FIG. **1** and described herein).

[0062] At an operation **506**, the vital signs information is processed via the prediction model. The processing, via the trained prediction model, generates (i) a first prediction related a clinical intervention need for the individual, (ii) sub predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related. The contributing sub-predictions correspond to respective ones of the weighted predictive parameter features. Processing also includes causing linking of the first prediction and the contributing sub-predictions based on the relatedness information and/or other information. In some embodiments, operation **506** is performed by a processor component the same as or similar to prediction component **26** (shown in FIG. **1** and described herein).

[0063] At an operation **508**, a prediction and/or predictions related to a clinical interventional need are generated. In some embodiments, the prediction model (described above) comprises a cardiovascular prediction model, a respiratory prediction model, and/or other models. In such embodiments, the prediction related to the clinical intervention need for the individual is a combination of a cardiovascular indicator determined based on weighted predictive cardiovascular parameter features and a respiratory indicator determined based on weighted predictive respiratory parameter features. As described above, these features may be weighted in such a way so as to cause the prediction to be

indicative of one or more specific outcomes of interest. In some embodiments, operation **508** is performed by a processor component the same as or similar to prediction component **26** (shown in FIG. **1** and described herein).

[0064] At an operation **510**, a presentation related to a clinical intervention need for the individual is caused. The presentation is caused, via a user interface, based on the linking and/or other information. The presentation comprises the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions. In some embodiments, the presentation related to a clinical intervention need for the individual is a risk score. The risk score may be indicative of a need for acute intervention and/or other information. In some embodiments, the individual (described above) comprises a plurality of individuals, and operation **510** includes displaying risk scores for the plurality of individuals. In some embodiments, operation **510** includes generating an ordered display representative of the plurality of individuals based on risk scores associated with the plurality of individuals. In some embodiments, operation **510** is performed by a processor component the same as or similar to presentation component **28** (shown in FIG. **1** and described herein).

[0065] In some embodiments, method **500** comprises continuously providing additional patient information as input to the prediction model to further train the prediction model for generating predictions related to a need for clinical intervention for individual patients. The further training of the prediction model may cause the prediction model to develop an updated set of weighted predictive parameter features, for example. The updated set may be developed by one or more of (i) modification of the weighted predictive parameter features, (ii) removal of at least one of the weighted predictive parameter features from the prediction model, (iii) development of one or more additional weighted predictive parameter features, (iv) modifying interaction terms and/or categories, and/or other operations. In some embodiments, method **500** comprises receiving (e.g., continuously and/or intermittently), via the one or more sensors, additional vital signs information for the one or more vital signs of the individual; and processing, via the further-trained prediction model, the additional vital signs information to generate (i) an additional prediction related to a clinical intervention need for the individual, (ii) additional sub-predictions contributing to the additional prediction or to at least another one of the additional sub-predictions, (iii) additional relatedness information indicating how the additional prediction and the contributing additional sub-predictions are related, and/or other information. The contributing additional sub-predictions correspond to respective ones of the weighted predictive parameter features of the updated set. In some embodiments, method **500** includes causing linking of the additional prediction and the contributing additional sub-predictions based on the additional relatedness information; and updating the user interface, based on the linking of the additional prediction and the contributing additional sub-predictions. The updated prediction comprises the additional prediction and the additional contributing sub-predictions such that user selection related to the additional prediction causes display of one or more of the contributing additional sub-predictions.

EXAMPLES

Example 1

[0066]

Logistic Regression Model of Heart Rate and Mean Arterial Blood Pressure Data Predicting CV Intervention or Death (n = 70,000).

Variables	Odds Ratio	P-value	95% Confidence Interval
hr_var1	3.642×10^{-7}	0.000	0.000, 0.000
hr_var2	1	.	1.000, 1.000
hr_var3	64.723	0.000	61.079, 68.585
map_var1	2.561×10^{7}	0.000	7.0×10^{6}, 9.3×10^{67}
map_var2	49.336	0.000	43.520, 55.929
map_var3	9.791	0.000	9.518, 10.072
0.hr_slope_cat#0.hr_dpm_cat	Ref	Ref	Ref
0.hr_slope_cat#1.hr_dpm_cat	0.716	0.010	0.557, 0.920
0.hr_slope_cat#2.hr_dpm_cat	0.469	0.000	0.356, 0.619
0.hr_slope_cat#8.hr_dpm_cat	2.378	0.000	2.262, 2.499
0.hr_slope_cat#9.hr_dpm_cat	4.617	0.000	4.381, 4.866
1.hr_slope_cat#0.hr_dpm_cat	2.019	0.000	1.919, 2.124
1.hr_slope_cat#1.hr_dpm_cat	4.938	0.000	3.827, 6.373
1.hr_slope_cat#2.hr_dpm_cat	1.449	0.011	1.095, 1.917
1.hr_slope_cat#8.hr_dpm_cat	4.685	0.000	4.363, 5.031
1.hr_slope_cat#9.hr_dpm_cat	6.621	0.000	6.067, 7.226
2.hr_slope_cat#0.hr_dpm_cat	1.472	0.000	1.404, 1.544
2.hr_slope_cat#1.hr_dpm_cat	1.981	0.000	1.529, 2.566
2.hr_slope_cat#2.hr_dpm_cat	0.855	0.278	0.646, 1.133
2.hr_slope_cat#8.hr_dpm_cat	3.476	0.000	3.244, 3.725
2.hr_slope_cat#9.hr_dpm_cat	6.240	0.000	5.764, 6.755
8.hr_slope_cat#0.hr_dpm_cat	1.131	0.000	1.079, 1.186
8.hr_slope_cat#1.hr_dpm_cat	0.422	0.000	0.312, 0.570
8.hr_slope_cat#2.hr_dpm_cat	0.388	0.000	0.291, 0.517
8.hr_slope_cat#8.hr_dpm_cat	2.597	0.000	2.428, 2.779
8.hr_slope_cat#9.hr_dpm_cat	5.207	0.000	4.849, 5.591
9.hr_slope_cat#0.hr_dpm_cat	1.258	0.000	1.206, 1.312
9.hr_slope_cat#1.hr_dpm_cat	0.480	0.000	0.353, 0.654
9.hr_slope_cat#2.hr_dpm_cat	0.256	0.000	0.190, 0.345
9.hr_slope_cat#8.hr_dpm_cat	3.149	0.000	2.962, 3.349
9.hr_slope_cat#9.hr_dpm_cat	4.528	0.000	4.260, 4.812
0.hr_dlp_cat#0.hr_dpm_cat	Ref	Ref	Ref
0.hr_dlp_cat#1.hr_dpm_cat	1.136	0.320	0.884, 1.460
0.hr_dlp_cat#2.hr_dpm_cat	1.469	0.007	1.115, 1.937
0.hr_dlp_cat#8.hr_dpm_cat	0.772	0.000	0.735, 0.812
0.hr_dlp_cat#9.hr_dpm_cat	0.942	0.029	0.893, 0.993
1.hr_dlp_cat#0.hr_dpm_cat	2.454	0.000	2.386, 2.524
1.hr_dlp_cat#1.hr_dpm_cat	7.698	0.000	5.994, 9.887
1.hr_dlp_cat#2.hr_dpm_cat	9.140	0.000	6.921, 12.069
1.hr_dlp_cat#8.hr_dpm_cat	1.211	0.000	1.139, 1.288
1.hr_dlp_cat#9.hr_dpm_cat	1.050	0.282	0.961, 1.147
2.hr_dlp_cat#0.hr_dpm_cat	1.048	0.000	1.040, 1.056
2.hr_dlp_cat#1.hr_dpm_cat	1.842	0.000	1.431, 2.369
2.hr_dlp_cat#2.hr_dpm_cat	1.696	0.000	1.287, 2.236
2.hr_dlp_cat#8.hr_dpm_cat	0.842	0.000	0.801, 0.885
2.hr_dlp_cat#9.hr_dpm_cat	1.083	0.004	1.027, 1.143
8.hr_dlp_cat#0.hr_dpm_cat	0.975	0.000	0.967, 0.983
8.hr_dlp_cat#1.hr_dpm_cat	0.952	0.702	0.740, 1.225
8.hr_dlp_cat#2.hr_dpm_cat	1.473	0.007	1.118, 1.942
8.hr_dlp_cat#8.hr_dpm_cat	0.757	0.000	0.720, 0.795
8.hr_dlp_cat#9.hr_dpm_cat	0.942	0.030	0.893, 0.994
9.hr_dlp_cat#0.hr_dpm_cat	1.264	0.000	1.170, 1.365
9.hr_dlp_cat#1.hr_dpm_cat	1	.	1.000, 1.000
9.hr_dlp_cat#2.hr_dpm_cat	1	.	1.000, 1.000
9.hr_dlp_cat#8.hr_dpm_cat	1	.	1.000, 1.000
9.hr_dlp_cat#9.hr_dpm_cat	1	.	1.000, 1.000
0.map_slope_cat#0.map_dpm_cat	Ref	Ref	Ref
0.map_slope_cat#1.map_dpm_cat	4.580	0.000	4.215, 4.975
0.map_slope_cat#2.map_dpm_cat	1.674	0.000	1.555, 1.803
0.map_slope_cat#8.map_dpm_cat	0.661	0.000	0.634, 0.689
0.map_slope_cat#9.map_dpm_cat	0.920	0.036	0.852, 0.994
1.map_slope_cat#0.map_dpm_cat	1.271	0.000	1.218, 1.326

-continued

Logistic Regression Model of Heart Rate and Mean Arterial Blood Pressure Data Predicting CV Intervention or Death (n = 70,000).

Variables	Odds Ratio	P-value	95% Confidence Interval
1.map_slope_cat#1.map_dpm_cat	4.954	0.000	4.520, 5.429
1.map_slope_cat#2.map_dpm_cat	1.780	0.000	1.636, 1.936
1.map_slope_cat#8.map_dpm_cat	0.893	0.000	0.841, 0.947
1.map_slope_cat#9.map_dpm_cat	1.234	0.000	1.130, 1.348
2.map_slope_cat#0.map_dpm_cat	0.979	0.415	0.931, 1.030
2.map_slope_cat#1.map_dpm_cat	4.617	0.000	4.192, 5.085
2.map_slope_cat#2.map_dpm_cat	1.605	0.000	1.468, 1.754
2.map_slope_cat#8.map_dpm_cat	0.671	0.000	0.627, 0.718
2.map_slope_cat#9.map_dpm_cat	1.066	0.226	0.962, 1.182
8.map_slope_cat#0.map_dpm_cat	1.040	0.113	0.991, 1.092
8.map_slope_cat#1.map_dpm_cat	4.072	0.000	3.694, 4.487
8.map_slope_cat#2.map_dpm_cat	1.870	0.000	1.711, 2.044
8.map_slope_cat#8.map_dpm_cat	0.658	0.000	0.619, 0.701
8.map_slope_cat#9.map_dpm_cat	0.929	0.084	0.855, 1.009
9.map_slope_cat#0.map_dpm_cat	1.386	0.000	1.330, 1.443
9.map_slope_cat#1.map_dpm_cat	5.294	0.000	4.815, 5.821
9.map_slope_cat#2.map_dpm_cat	2.947	0.000	2.706, 3.210
9.map_slope_cat#8.map_dpm_cat	0.820	0.000	0.778, 0.863
9.map_slope_cat#9.map_dpm_cat	0.908	0.000	0.861, 0.957
0.map_dlp_cat#0.map_dpm_cat	Ref	Ref	Ref
0.map_dlp_cat#1.map_dpm_cat	1.535	0.000	1.415, 1.666
0.map_dlp_cat#2.map_dpm_cat	1.512	0.000	1.405, 1.627
0.map_dlp_cat#8.map_dpm_cat	0.757	0.000	0.730, 0.784
0.map_dlp_cat#9.map_dpm_cat	0.639	0.000	0.605, 0.674
1.map_dlp_cat#0.map_dpm_cat	0.442	0.000	0.435, 0.449
1.map_dlp_cat#1.map_dpm_cat	0.914	0.034	0.841, 0.992
1.map_dlp_cat#2.map_dpm_cat	0.599	0.000	0.555, 0.646
1.map_dlp_cat#8.map_dpm_cat	0.398	0.000	0.370, 0.427
1.map_dlp_cat#9.map_dpm_cat	0.430	0.000	0.367, 0.503
2.map_dlp_cat#0.map_dpm_cat	0.766	0.000	0.759, 0.772
2.map_dlp_cat#1.map_dpm_cat	1.388	0.000	1.279, 1.508
2.map_dlp_cat#2.map_dpm_cat	1.112	0.006	1.033, 1.197
2.map_dlp_cat#8.map_dpm_cat	0.631	0.000	0.604, 0.659
2.map_dlp_cat#9.map_dpm_cat	0.458	0.000	0.413, 0.507
8.map_dlp_cat#0.map_dpm_cat	0.954	0.000	0.947, 0.961
8.map_dlp_cat#1.map_dpm_cat	1.907	0.000	1.756, 2.072
8.map_dlp_cat#2.map_dpm_cat	1.569	0.000	1.457, 1.689

-continued

Logistic Regression Model of Heart Rate and Mean Arterial Blood Pressure Data Predicting CV Intervention or Death (n = 70,000).

Variables	Odds Ratio	P-value	95% Confidence Interval
8.map_dlp_cat#8.map_dpm_cat	0.774	0.000	0.747, 0.803
8.map_dlp_cat#9.map_dpm_cat	0.623	0.000	0.591, 0.657
9.map_dlp_cat#0.map_dpm_cat	0.739	0.000	0.723, 0.756
9.map_dlp_cat#1.map_dpm_cat	1	.	1.000, 1.000
9.map_dlp_cat#2.map_dpm_cat	1	.	1.000, 1.000
9.map_dlp_cat#8.map_dpm_cat	1	.	1.000, 1.000
9.map_dlp_cat#9.map_dpm_cat	1	.	1.000, 1.000
0.hr_slope_cat#0.map_slope_cat	Ref	Ref	Ref
0.hr_slope_cat#1.map_slope_cat	0.659	0.000	0.632, 0.688
0.hr_slope_cat#2.map_slope_cat	0.931	0.007	0.885, 0.979
0.hr_slope_cat#8.map_slope_cat	0.974	0.286	0.927, 1.022
0.hr_slope_cat#9.map_slope_cat	0.843	0.000	0.809, 0.878
1.hr_slope_cat#0.map_slope_cat	1.006	0.824	0.951, 1.065
1.hr_slope_cat#1.map_slope_cat	0.999	0.969	0.954, 1.046
1.hr_slope_cat#2.map_slope_cat	1.108	0.001	1.044, 1.174
1.hr_slope_cat#8.map_slope_cat	0.903	0.002	0.849, 0.960
1.hr_slope_cat#9.map_slope_cat	1	.	1.000, 1.000
2.hr_slope_cat#0.map_slope_cat	0.999	0.976	0.949, 1.052
2.hr_slope_cat#1.map_slope_cat	0.792	0.000	0.758, 0.827
2.hr_slope_cat#2.map_slope_cat	1.032	0.250	0.978, 1.090
2.hr_slope_cat#8.map_slope_cat	1.023	0.416	0.969, 1.080
2.hr_slope_cat#9.map_slope_cat	1	.	1.000, 1.000
8.hr_slope_cat#0.map_slope_cat	1.138	0.000	1.083, 1.197
8.hr_slope_cat#1.map_slope_cat	0.928	0.001	0.887, 0.970
8.hr_slope_cat#2.map_slope_cat	1.137	0.000	1.076, 1.201
8.hr_slope_cat#8.map_slope_cat	1.139	0.000	1.081, 1.200
8.hr_slope_cat#9.map_slope_cat	1	.	1.000, 1.000
9.hr_slope_cat#0.map_slope_cat	1	.	1.000, 1.000
9.hr_slope_cat#1.map_slope_cat	1	.	1.000, 1.000
9.hr_slope_cat#2.map_slope_cat	1	.	1.000, 1.000
9.hr_slope_cat#8.map_slope_cat	1	.	1.000, 1.000
9.hr_slope_cat#9.map_slope_cat	1	.	1.000, 1.000

Example 2

[0067]

Criteria For Categorizing HR and MAP Slope, Deviation from Population Mean, and Deviation from Linear Projection Covariates

	HR			MAP		
Category	Slope for HR (/min)	Deviation from population mean	Deviation from linear projection	Slope for MAP (/min)	Deviation from population mean	Deviation from linear projection
9	≥.33	≥30	≥20	≥.0625	≥20	≥20
8	.167. to .32	>0 to <30	>0 to <20	.02083 to .0624	>0 to <20	>0 to <20
0	−.168 to .166	0	0	−.02084 to .02082	0	0
2	−.34 to −.167	>−15 to <0	>−10 to <0	−.0626 to −.02083	>−10 to <0	>−10 to <0
1	≤−.33	≤−15	≤−10	≤−.0625	≤−10	≤−10

[0068] In the claims, any reference signs placed between parentheses shall not be construed as limiting the claim. The word "comprising" or "including" does not exclude the presence of elements or steps other than those listed in a claim. In a device claim enumerating several means, several of these means may be embodied by one and the same item of hardware. The word "a" or "an" preceding an element does not exclude the presence of a plurality of such elements. In any device claim enumerating several means, several of these means may be embodied by one and the same item of hardware. The mere fact that certain elements are recited in mutually different dependent claims does not indicate that these elements cannot be used in combination.

[0069] Although the description provided above provides detail for the purpose of illustration based on what is currently considered to be the most practical and preferred embodiments, it is to be understood that such detail is solely for that purpose and that the disclosure is not limited to the expressly disclosed embodiments, but, on the contrary, is intended to cover modifications and equivalent arrangements that are within the spirit and scope of the appended claims. For example, it is to be understood that the present disclosure contemplates that, to the extent possible, one or more features of any embodiment can be combined with one or more features of any other embodiment.

1. A system configured to provide a layer-based presentation of a model-generated patient-related prediction, the system comprising one or more hardware processors configured by machine readable instructions to:

provide patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the training of the prediction model causing the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, patient demographic information, patient physiology, patient laboratory data, a patient diagnosis, or patient treatment data, the patient information comprising initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments;

receive, via one or more sensors, vital signs information for one or more vital signs of an individual;

process, via the trained prediction model, the received information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features;

cause linking of the first prediction and the contributing sub-predictions based on the relatedness information; and

cause, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions,

wherein the prediction model comprises a cardiovascular prediction model and a respiratory prediction model and wherein the presentation related to the clinical intervention need for the individual is configured such that the first prediction is a combination of a cardiovascular indicator sub-prediction determined based on weighted predictive cardiovascular parameter features and a respiratory indicator sub-prediction determined based on weighted predictive respiratory parameter features.

2. The system of claim **1**, wherein the one or more hardware processors are configured to:

intermittently, in a retrospective fashion, provide additional patient information as input to the prediction model to further train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the further training of the prediction model causing the prediction model to develop an updated set of weighted predictive parameter features, the updated set being developed by one or more of (i) modification of the weighted predictive parameter features, (ii) removal of at least one of the weighted predictive parameter features from the prediction model, or (iii) development of one or more additional weighted predictive parameter features;

receive, via the one or more sensors, additional vital signs information for the one or more vital signs of the individual;

process, via the further-trained prediction model, the additional vital signs information to generate (i) an additional prediction related to a clinical intervention need for the individual, (ii) additional sub-predictions contributing to the additional prediction or to at least another one of the additional sub-predictions, (iii) additional relatedness information indicating how the additional prediction and the contributing additional sub-predictions are related, the contributing additional sub-predictions corresponding to respective ones of the weighted predictive parameter features of the updated set;

cause linking of the additional prediction and the contributing additional sub-predictions based on the additional relatedness information; and

update, via the user interface, based on the linking of the additional prediction and the contributing additional sub-predictions, the presentation related to a clinical intervention need for the individual, the updated prediction comprising the additional prediction and the additional contributing sub-predictions such that user selection related to the additional prediction causes display of one or more of the contributing additional sub-predictions.

3. The system of claim **1**, wherein the one or more hardware processors are configured such that the weighted predictive parameter features include one or more of:

an amount of variability in a given vital sign;

a slope for the given vital sign determined based on values of the given vital sign over time;

an amount of deviation from a baseline for the given vital sign; or

an amount of deviation from an expected level of the given vital sign for the individual.

4. The system of claim **1**, wherein the one or more hardware processors are configured such that the presentation related to a clinical intervention need for the individual is a risk score, the risk score indicative of a need for acute

intervention, wherein the individual is continuously monitored via the one or more sensors, and wherein the risk score is continuously updated.

5. The system of claim **4**, wherein the one or more hardware processors are configured such that the individual comprises a plurality of individuals; wherein the one or more hardware processors are further configured to generate an ordered display representative of the plurality of individuals based on risk scores associated with the plurality of individuals.

6. The system of claim **1**, wherein the one or more hardware processors are configured such that the prediction model is derived from a logistical regression statistical model.

7. The system of claim **1**, further comprising the one or more sensors configured to generate output signals that convey the vital signs information, the one or more sensors comprising a cardiovascular sensor and a respiratory sensor operatively coupled to the individual.

8. (canceled)

9. A method for providing a layer-based presentation of a model-generated patient-related prediction with a prediction system, the system comprising one or more hardware processors configured by machine readable instructions, the method comprising:

providing patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the training of the prediction model causing the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, patient demographic information, patient physiology, patient laboratory data, a patient diagnosis, or patient treatment data, the patient information comprising initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments;

receiving, via one or more sensors, vital signs information for one or more vital signs of an individual;

processing, via the trained prediction model, the received information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features;

causing linking of the first prediction and the contributing sub-predictions based on the relatedness information; and

causing, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions,

wherein the prediction model comprises a cardiovascular prediction model and a respiratory prediction model and wherein the presentation related to the clinical intervention need for the individual is configured such that the first prediction is a combination of a cardiovascular indicator sub-prediction determined based on weighted predictive cardiovascular parameter features and a respiratory indicator sub-prediction determined based on weighted predictive respiratory parameter features.

10. The method of claim **9**, further comprising:

intermittently, in a retrospective fashion, providing additional patient information as input to the prediction model to further train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the further training of the prediction model causing the prediction model to develop an updated set of weighted predictive parameter features, the updated set being developed by one or more of (i) modification of the weighted predictive parameter features, (ii) removal of at least one of the weighted predictive parameter features from the prediction model, or (iii) development of one or more additional weighted predictive parameter features;

receiving, via the one or more sensors, additional vital signs information for the one or more vital signs of the individual;

processing, via the further-trained prediction model, the additional vital signs information to generate (i) an additional prediction related to a clinical intervention need for the individual, (ii) additional sub-predictions contributing to the additional prediction or to at least another one of the additional sub-predictions, (iii) additional relatedness information indicating how the additional prediction and the contributing additional sub-predictions are related, the contributing additional sub-predictions corresponding to respective ones of the weighted predictive parameter features of the updated set;

causing linking of the additional prediction and the contributing additional sub-predictions based on the additional relatedness information; and

updating, via the user interface, based on the linking of the additional prediction and the contributing additional sub-predictions, the presentation related to a clinical intervention need for the individual, the updated prediction comprising the additional prediction and the additional contributing sub-predictions such that user selection related to the additional prediction causes display of one or more of the contributing additional sub-predictions.

11. The method of claim **9**, wherein the weighted predictive parameter features include one or more of:

an amount of variability in a given vital sign;

a slope for the given vital sign determined based on values of the given vital sign over time;

an amount of deviation from a baseline for the given vital sign; or

an amount of deviation from an expected level of the given vital sign for the individual.

12. The method of claim **9**, wherein the presentation related to a clinical intervention need for the individual is a risk score, the risk score indicative of a need for acute intervention, wherein the individual is continuously monitored via the one or more sensors, and wherein the risk score is continuously updated.

13. The method of claim **12**, wherein the individual comprises a plurality of individuals; the method further comprising generating an ordered display representative of

the plurality of individuals based on risk scores associated with the plurality of individuals.

14. The method of claim **9**, further comprising generating, with the one or more sensors, output signals that convey the vital signs information, the one or more sensors comprising a cardiovascular sensor and a respiratory sensor operatively coupled to the individual.

15. (canceled)

16. A system configured to provide a layer-based presentation of a model-generated patient-related prediction, the system comprising:

means for providing patient information as input to a prediction model to train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the training of the prediction model causing the prediction model to develop weighted predictive parameter features that correspond to patient vital signs, patient demographic information, patient physiology, patient laboratory data, a patient diagnosis, or patient treatment data, the patient information comprising initial vital signs of patients, treatments provided to the patients with the respective initial vital signs, and respective vital signs resulting from the treatments;

means for receiving, via one or more sensors, vital signs information for one or more vital signs of an individual;

means for processing, via the trained prediction model, the received information to generate (i) a first prediction related a clinical intervention need for the individual, (ii) sub-predictions contributing the first prediction or to at least another one of the sub-predictions, and (iii) relatedness information indicating how the first prediction and the contributing sub-predictions are related, the contributing sub-predictions corresponding to respective ones of the weighted predictive parameter features;

means for causing linking of the first prediction and the contributing sub-predictions based on the relatedness information; and

means for causing, via a user interface, based on the linking, a presentation related to a clinical intervention need for the individual, the presentation comprising the first prediction and the contributing sub-predictions such that user selection related to the first prediction causes display of one or more of the contributing sub-predictions,

wherein the prediction model comprises a cardiovascular prediction model and a respiratory prediction model and wherein the presentation related to the clinical intervention need for the individual is configured such that the first prediction is a combination of a cardiovascular indicator sub-prediction determined based on weighted predictive cardiovascular parameter features and a respiratory indicator sub-prediction determined based on weighted predictive respiratory parameter features.

17. The system of claim **16**, further comprising:

means for intermittently, in a retrospective fashion, providing additional patient information as input to the prediction model to further train the prediction model for generating predictions related to a need for clinical intervention for individual patients, the further training of the prediction model causing the prediction model to develop an updated set of weighted predictive parameter features, the updated set being developed by one or more of (i) modification of the weighted predictive parameter features, (ii) removal of at least one of the weighted predictive parameter features from the prediction model, or (iii) development of one or more additional weighted predictive parameter features;

means for receiving, via the one or more sensors, additional vital signs information for the one or more vital signs of the individual;

means for processing, via the further-trained prediction model, the additional vital signs information to generate (i) an additional prediction related to a clinical intervention need for the individual, (ii) additional sub-predictions contributing to the additional prediction or to at least another one of the additional sub-predictions, (iii) additional relatedness information indicating how the additional prediction and the contributing additional sub-predictions are related, the contributing additional sub-predictions corresponding to respective ones of the weighted predictive parameter features of the updated set;

means for causing linking of the additional prediction and the contributing additional sub-predictions based on the additional relatedness information; and

means for updating, via the user interface, based on the linking of the additional prediction and the contributing additional sub-predictions, the presentation related to a clinical intervention need for the individual, the updated prediction comprising the additional prediction and the additional contributing sub-predictions such that user selection related to the additional prediction causes display of one or more of the contributing additional sub-predictions.

18. The system of claim **16**, wherein the weighted predictive parameter features include one or more of:

an amount of variability in a given vital sign;

a slope for the given vital sign determined based on values of the given vital sign over time;

an amount of deviation from a baseline for the given vital sign; or

an amount of deviation from an expected level of the given vital sign for the individual.

19. The system of claim **16**, wherein the presentation related to a clinical intervention need for the individual is a risk score, the risk score indicative of a need for acute intervention, wherein the individual is continuously monitored via the one or more sensors, and wherein the risk score is continuously updated.

20. The system of claim **16**, further comprising the one or more sensors, the one or more sensors configured to generate output signals that convey the vital signs information, the one or more sensors comprising a cardiovascular sensor and a respiratory sensor operatively coupled to the individual.

* * * * *

专利名称(译)	用于提供模型生成的患者相关预测的基于层的表示的系统和方法		
公开(公告)号	US20200176114A1	公开(公告)日	2020-06-04
申请号	US16/613007	申请日	2018-05-25
[标]申请(专利权)人(译)	皇家飞利浦电子股份有限公司		
申请(专利权)人(译)	皇家飞利浦N.V.		
当前申请(专利权)人(译)	皇家飞利浦N.V.		
[标]发明人	BADAWI OMAR SWAMI SUNIL LIU XINGGANG GAO XI HASSAN ERKAN		
发明人	BADAWI, OMAR AMELUNG, PAMELA JAYNE SWAMI, SUNIL LIU, XINGGANG GAO, XI HASSAN, ERKAN		
IPC分类号	G16H50/20 G16H40/63 A61B5/00 G16H50/30		
CPC分类号	G16H50/30 A61B5/0002 A61B5/7275 G16H50/20 G16H40/63		
优先权	62/512361 2017-05-30 US		
外部链接	Espacenet USPTO		

摘要(译)

本系统被配置为将患者信息作为输入提供给预测模型，以训练该预测模型以生成与针对个体患者的临床干预需求有关的预测。 该系统被配置为接收个人的一个或多个生命体征的生命体征信息。 该系统被配置为通过训练后的预测模型处理生命体征信息，以生成（i）与个体的临床干预需求相关的第一预测，（ii）对第一预测有贡献或对至少另一个做出贡献的子预测。 （iii）指示第一预测与贡献子预测如何相关的相关性信息，贡献子预测分别与加权预测参数特征中的每个相对应。 该系统被配置为基于模型的输出来引起与针对个人的临床干预需求有关的呈现。