CONTINUOUS OBSERVATION AND MONITORING FOR PATIENT ASSESSMENT USING A SENSOR-BASED SYSTEM

CROSS REFERENCE TO RELATED APPLICATION

[0001] This application claims the benefit of U.S. Provisional App. No. 63/566,066, filed March 15, 2024, which is incorporated herein by reference in its entirety for all purposes.

GOVERNMENT SUPPORT CLAUSE

[0002] This invention was made with government support under Grant No. RERC STARS # 90REG E0010 awarded by National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) and under Grant No. P2CHD101899 awarded by National Institutes of Health (NIH). The government has certain rights in the invention.

FIELD

[0003] The present disclosure relates generally to patient monitoring systems. More specifically, the disclosure relates to patient monitoring systems that implement wearable sensors for continuous monitoring and observation.

BACKGROUND

[0004] Monitoring patient health is important in keeping track of the patient's progress in treatment, therapy, and rehabilitation. However, when the patient is outside of the hospital or other healthcare or medical facility, it is difficult to maintain a reliable means of continuously observing or monitoring the patient's health. Furthermore, it takes time and effort by doctors and physicians to review the monitoring data obtained from the patients. Every day, clinicians manually inspect, analyze, and log wide-ranging information related to their patients' physical and mental health. Many of these practices require substantial labor (e.g., measuring patterns in an electrocardiogram using physical or digital calipers), which is time-intensive and susceptible to human error. Other practices rely on subjective, observational tests (e.g., assessing a patient's ability to perform day-to-day activities

using graded scores), which require specialized training and are subject to inter- and intra-rater variability issues, even among trained experts. Improving the efficiency of these practices becomes more urgent as the population ages and we are faced with an extensive shortage of physicians and therapists, and based on the rising prevalence of clinician burnout and its severe consequences.

[0005] As such, there is a need for a computing system that is capable of continuously observing and monitoring the patients' health in order to provide doctors and physicians with detailed insight into each patient's recovery journey.

SUMMARY

[0006] Disclosed herein are systems for substantially continuous monitoring and assessment of patient health. A system for continuous monitoring and assessment of patient health includes: at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate new sensor data associated with the patient; and a data system comprising a database and at least one data processing device. The data processing device is configured to: collect historical data associated with other patients from the database; train and validate at least one predictive model based on the historical data; extract features from the new sensor data received from the sensor device; assess, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and transmit the clinical outcomes to be reviewed by the patient or a clinician of the patient.

[0007] Also disclosed herein are methods, such as computer-implemented methods, for substantially continuously monitoring and assessing patient health. The method includes: collecting historical data associated with other patients from a database; training and validating at least one predictive model based on the historical data; extracting features from new sensor data received from at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate the new sensor data associated with the patient; assessing, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and transmitting the clinical outcomes to be reviewed by the patient or a clinician of the patient. Further disclosed herein are non-

transitory computer readable media storing computer program instructions that, when executed by a processor, cause the processor to perform the aforementioned computer-implemented methods.

[0008] In one example ("Example 1"), a system for continuous monitoring and assessment of patient health includes: at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate new sensor data associated with the patient; and a data system comprising a database and at least one data processing device. The data processing device is configured to: collect historical data associated with other patients from the database; train and validate at least one predictive model based on the historical data; extract features from the new sensor data received from the sensor device; assess, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and transmit the clinical outcomes to be reviewed by the patient or a clinician of the patient.

[0009] In another example ("Example 2") further to Example 1, the data processing device is further configured to refine the trained and validated model using the new sensor data.

[0010] In another example ("Example 3") further to Example 1 or 2, the system includes at least one user device operatively coupled with the sensor device, and the user device is configured to receive the new sensor data from the sensor device and transmit the new sensor data to the data processing device.

[0011] In another example ("Example 4") further to Example 3, the user device is further configured to receive the clinical outcomes from the data processing device and display the clinical outcomes to be reviewed by the patient or the clinician.

[0012] In another example ("Example 5") further to Example 3 or 4, the user device is further configured to turn off or set to standby the sensor device in response to detecting detachment of the sensor device from the patient.

[0013] In another example ("Example 6") further to Example 3 or 4, the user device is further configured to turn off or set to standby the sensor device in response to detecting malfunctioning of the sensor device.

[0014] In another example ("Example 7") further to any one of Examples 1-6, the new sensor data includes one or more types of biometric or activity data.

[0015] In another example ("Example 8") further to Example 7, the biometric or activity data includes one or more of: motion data from one or more inertial measurement units (IMUs), muscle activity data from electromyography (EMG), heart activity data from electrocardiography (ECG), or physiological signal data from photoplethysmography (PPG).

[0016] In another example ("Example 9") further to Example 7, the extracted features include one or more of: a step velocity obtained from the IMUs, a heart rate variability obtained from the ECG, or a maximum voluntary contraction obtained from the EMG.

[0017] In another example ("Example 10") further to any one of Examples 7-9, the new sensor data further includes one or more contextual information associated with an environment in which the patient is located.

[0018] In another example ("Example 11") further to any one of Examples 7-9, the new sensor data is generated at a sampling rate that is adjustable based on user input.

[0019] In another example ("Example 12") further to any one of Examples 1-11, the data processing device is configured to extract the features from the new sensor data received from the sensor device by: processing the new sensor data in or near real-time to reduce noise from the new sensor data, and extracting the features from the processed sensor data.

[0020] In another example ("Example 13") further to Example 12, the data processing device is further configured to perform data segmentation and data transformation offline in response to recording the new sensor data in the database.

[0021] In another example ("Example 14") further to any one of Examples 1-13, the extracted features include one or more of: mathematical moments, root-mean-square values, entropy, or frequency characteristics that are associated with the patient.

[0022] In another example ("Example 15") further to any one of Examples 1-14, the at least one predictive model is trained using sensor recordings, demographics, and clinical outcomes that are associated with the historical data.

[0023] In another example ("Example 16") further to any one of Examples 1-15, the clinical outcomes associated with the patient include one or more of: projected

level of functional independence for the patient, predicted ambulation ability of the patient, predicted risk of falling for the patient, or predicted overall recovery or recovery trajectories for the patient.

[0024] In one example ("Example 17"), a method for continuously monitoring and assessing patient health includes: collecting historical data associated with other patients from a database; training and validating at least one predictive model based on the historical data; extracting features from new sensor data received from at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate the new sensor data associated with the patient; assessing, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and transmitting the clinical outcomes to be reviewed by the patient or a clinician of the patient.

[0025] In one example ("Example 18"), a non-transitory computer readable medium stores computer program instructions that, when executed by a processor, cause the processor to: collect historical data associated with other patients from a database; train and validate at least one predictive model based on the historical data; extract features from new sensor data received from at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate the new sensor data associated with the patient; assess, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and transmit the clinical outcomes to be reviewed by the patient or a clinician of the patient.

[0026] The foregoing examples are just that, and should not be read to limit or otherwise narrow the scope of any of the inventive concepts otherwise provided by the instant disclosure. While multiple examples are disclosed, still other embodiments will become apparent to those skilled in the art from the following detailed description, which shows and describes illustrative examples. Accordingly, the drawings and detailed description are to be regarded as illustrative in nature rather than restrictive in nature.

BRIEF DESCRIPTION OF THE DRAWINGS

[0027] The accompanying drawings are included to provide a further understanding of the embodiments of the disclosure and are incorporated in and constitute a part of this specification, illustrate examples, and together with the description serve to explain the principles of the disclosure.

[0028] FIG. 1 is a schematic diagram of a patient health monitoring and assessment system according to embodiments disclosed herein;

[0029] FIG. 2 is a flow chart of a process performed by a processing device in the patient health monitoring and assessment system according to embodiments disclosed herein;

[0030] FIG. 3 is another flow chart of a process performed by a processing device in the patient health monitoring and assessment system according to embodiments disclosed herein;

[0031] FIG. 4 is a block diagram of the processing devices as implemented in the patient health monitoring and assessment system according to embodiments disclosed herein;

[0032] FIG. 5 is a flow diagram of an Integrated Automate-Illuminate-Predict (AIP) framework according to embodiments disclosed herein;

[0033] FIG. 6 is a graph comparing the illuminative sensor measurements of the AIP framework as compared to traditional measurements according to embodiments disclosed herein; and

[0034] FIG. 7 is a graph comparing a predictive treatment response relative to a known standard of care according to embodiments disclosed herein.

[0035] It should be understood that some of the drawings and replicas of the photographs may not necessarily be shown to scale, unless otherwise indicated. In certain instances, details that are not necessary for an understanding of the disclosure or that render other details difficult to perceive may have been omitted. It should be understood, of course, that the disclosure is not necessarily limited to the particular examples or embodiments illustrated or depicted herein.

DETAILED DESCRIPTION

Definitions and Terminology

[0036] This disclosure is not meant to be read in a restrictive manner. For example, the terminology used in the application should be read broadly in the context of the meaning those in the field would attribute such terminology. For example, in some embodiments, "continuous" monitoring of patient health can be understood as "uninterrupted" or "constant" monitoring. In other examples, monitoring of patient health may still be considered "continuous" even if there are short periods of interruption. Persons skilled in the art will readily appreciate that the various embodiments of the inventive concepts provided in the present disclosure can be realized by any number of methods and apparatuses configured to perform the intended functions. It should also be noted that the accompanying figures referred to herein are not necessarily drawn to scale, but may be exaggerated to illustrate various aspects of the present disclosure, and in that regard, the figures should not be construed as limiting. Some figures do, however, represent anatomy and the positioning of embodiments relative to that anatomy and such representations should be understood to be scaled and positioned accurately, with some deviation permitted as the anatomical structures depicted will vary in size and position from person to person.

[0037] With respect to terminology of inexactitude, the terms "about" and "approximately" may be used, interchangeably, to refer to a measurement that includes the stated measurement and that also includes any measurements that are reasonably close to the stated measurement. Measurements that are reasonably close to the stated measurement deviate from the stated measurement by a reasonably small amount as understood and readily ascertained by individuals having ordinary skill in the relevant arts. Such deviations may be attributable to measurement error, differences in measurement and/or manufacturing equipment calibration, human error in reading and/or setting measurements, minor adjustments made to optimize performance and/or structural parameters in view of differences in measurements associated with other components, particular implementation scenarios, imprecise adjustment and/or manipulation of objects by a person or machine, and/or the like, for example. In the event it is determined that individuals having ordinary skill in the relevant arts would not readily ascertain values for such

reasonably small differences, the terms "about" and "approximately" can be understood to mean plus or minus 10% of the stated value.

[0038] The phrases "at least one", "one or more", and "and/or" are open-ended expressions that are both conjunctive and disjunctive in operation. For example, each of the expressions "at least one of A, B and C", "at least one of A, B, or C", "one or more of A, B, and C", "one or more of A, B, or C" and "A, B, and/or C" means A alone, B alone, C alone, A and B together, A and C together, B and C together, or A, B and C together. When each one of A, B, and C in the above expressions refers to an element, such as X, Y, and Z, or class of elements, such as X_1-X_n, Y_1-Y_m, and Z_1-Z_o, the phrase is intended to refer to a single element selected from X, Y, and Z, a combination of elements selected from the same class (e.g., X_1 and X_2) as well as a combination of elements selected from two or more classes (e.g., Y_1 and Z_o).

[0039] It should be understood that every maximum numerical limitation given throughout this disclosure is deemed to include each and every lower numerical limitation as an alternative, as if such lower numerical limitations were expressly written herein. Every minimum numerical limitation given throughout this disclosure is deemed to include each and every higher numerical limitation as an alternative, as if such higher numerical limitations were expressly written herein. Every numerical range given throughout this disclosure is deemed to include each and every narrower numerical range that falls within such broader numerical range, as if such narrower numerical ranges were all expressly written herein.

[0040] Before any embodiments of the disclosure are explained in detail, it is to be understood that the disclosure is not limited in its application to the details of construction and the arrangement of components set forth in the following description or illustrated in the following drawings. The disclosure is capable of other embodiments and of being practiced or of being carried out in various ways. Also, it is to be understood that the phraseology and terminology used herein is for the purpose of description and should not be regarded as limiting. The use of "including," "comprising," or "having" and variations thereof herein is meant to encompass the items listed thereafter and equivalents thereof as well as additional items.

Description of Various Embodiments

[0041] The present disclosure relates to systems, devices, and methods for providing substantially continuous monitoring and assessment of patient health using one or more sensors that are wearably or noninvasively attached to the patient's body, as further explained herein. Wearable sensors have been heralded as revolutionary tools for healthcare. However, while data are easily acquired from sensors, users still grapple with questions about how sensors can meaningfully inform everyday clinical practice and research. To address this, a simple, comprehensive framework for utilizing sensor data in healthcare is disclosed herein. The framework includes processes that are applied together or separately to: (1) automate traditional clinical measurements, (2) illuminate novel correlations of disease and impairment, and (3) predict current and future outcomes, referred to herein as an "automate-illuminate-predict" framework, or AIP framework. The systems as disclosed herein may leverage non-invasive body-worn sensors for continuous monitoring and assessment of various neurological conditions, including but not limited to: stroke, Parkinson's disease, multiple sclerosis, and other movement disorders. The system may enable healthcare professionals such as clinicians and therapists to obtain traditional clinical measurements and new measurements of patient health/function from the sensor data. The system may use signal processing and machine learning to analyze biometric and activity data from the sensors, quantify a patient's physical impairments, and predict their current or future recovery status.

[0042] FIG. 1 shows an example of a system 100 that is configured to substantially continuously monitor and assess patient health for a plurality of patients as well as to provide assessment data such as clinical outcome predictions for review by the patient and/or the clinician associated with the patient. The system 100 includes a plurality of patients (e.g., Patient A, Patient B, and Patient C) as well as a sensor device 102 wearably attached to the body of each patient, such as to the limb(s) or torso of the patient, for example. Although only three patients are shown in the figure, it is to be understood that any suitable number of patients may be associated with and monitored by the system. The sensor device 102 may include one or more sensors that each takes a specific measurement with respect to the

patient. In some examples, the sensor device 102 may be operatively coupled with a user device 104 to which the sensor device 102 transmits the sensor data as measured. In some examples, the sensor data as measured may be stored locally, such as in a memory unit of the sensor device 102, such that the data may be transmitted to the user device 104. The transmitting may take place at a predetermined interval of time or when sufficient amount of data has been measured and collected, for efficiency. In some examples, the sensor device 102 and the user device 104 may be a single unit or component. In some examples, multiple sensor devices 102 may be associated with a single user device 104. In some examples, multiple sensor devices 102 may be worn by a single patient to monitor different measurements associated with the patient.

[0043] The sensor devices 102 or the user device 104 are communicably coupled with one or more networks 106 which may be any type of secured network or combination of secured networks that allows for encrypted communication between devices. In some embodiments, the network 106 can include one or more of: a local area network (LAN), wide area network (WAN), the Internet, cloud network, cellular network, mesh network, peer-to-peer (P2P) communication link, Bluetooth and/or some combination thereof and can include any number of wired or wireless links. Communication over the network 106 can be accomplished, for instance, via a network interface using any type of protocol, protection scheme, encoding, format, and/or packaging, as suitable, to preserve patient data privacy and security. Also communicably coupled with the network 106 is a data system 108 that includes a database 110 (e.g., a remote server) that stores thereon information associated with past and current patients, and a data processing device(s) 112 that is operably coupled with the database 110, such that the database 110, the data processing device(s) 112, and the user device(s) 104 may all be located at different locations separate from each other. As such, the system 100 facilitates continuous monitoring of patients either in-person or remotely, thus capable of facilitating comprehensive patient tracking across healthcare settings, from inpatient care (e.g., healthcare or medical facility admission through discharge) to outpatient treatment and community living, which is also beneficial for tracking the progress of rehabilitation. Advantageously, the system 100 can enhance the precision and effectiveness of

monitoring as well as refining treatment strategies, leading to more personalized and effective patient care a way to precision medicine, as further explained herein. In some examples, data system 106 may be a data system of a large-scale medical facility such as a hospital. In other examples, data system 106 may be a data system of a rehabilitation center or other healthcare facility that provides patient care.

[0044] As an illustrative example, the system 100 may facilitate a holistic monitoring approach, capturing both in-healthcare facility (e.g., in-hospital, in-rehabilitation facility, etc.) and community-based recovery using wearable sensor devices. After patients are admitted to a healthcare or medical facility, clinicians can electronically register a patient though the system. One or more wearable sensor devices are placed on the patient to acquire biometric and activity signal data. The patient's recovery status is dynamically updated and can be viewed on a digital patient dashboard (e.g., on the user device 104), allowing clinicians to track and analyze the patient's recovery status over time. Using these insights, healthcare professionals can provide tailored clinical care, resources, and guidance to patients and their families. Even after the patient is discharged from the healthcare or medical facility, the system 100 enables clinicians to similarly track recovery in the outpatient and community settings, further informing the patient's long-term care.

[0045] A wearable sensor device is a device worn on the body that measures biophysical data, such as vital signs (e.g., heart rate, blood pressure, temperature), bioelectrical signals (e.g., electromyography or EMG, electrocardiography or ECG, electroencephalography or EEG), motion (e.g., acceleration, rotation, proximity), and/or chemistry (e.g., glucose, sodium, potassium), as well as any suitable combination thereof. In some examples, the sensor devices 102 may transmit the sensor data to the user devices 104 via a wired connection or via a wireless connection such as using radiofrequency, including but not limited to Bluetooth, radiofrequency identification (RFID), near-field communication (NFC), etc., as suitable, and the user devices 104 may transmit the sensor data to the database 110 or the data processing device 112 via the network 106. In some examples, the sensor devices 102 may directly transmit the sensor data to the database 110 or the data processing device 112 via the network 106, for example when the sensor device 102 and the user device 104 are implemented as a single unit or component.

[0046] As referred to herein, a sensor device 102 may include one or more sensors capable of taking measurements associated with biometric signals or activity signals. The sensors may include any type of mechanical, electrical, optical or other sensor, including but not limited to inertial measurement units (IMUs), muscle activity sensors implementing electromyography (EMG), heart activity sensors implementing electrocardiography (ECG), physiological signal sensors implementing photoplethysmography (PPG), etc. In some examples, the sensor device 102 and/or the user device 104 may provide contextual information in addition to the sensor data, for example information associated with the patient's environment or location, which may be provided using a video camera or location monitor such as via global positioning system (GPS).

[0047] As referred to herein, a user device 104 may be any suitable computing device including but not limited to a mobile telephone (smartphone), laptop computer, tablet computer, desktop computer, server computer, personal computer, or any other mobile device capable of performing data processing. In some examples, the wearable sensor device 102 and the user device 104 are implemented as a single unit (e.g., in a single housing or casing) or separate units (e.g., different devices that are independently operable) as suitable.

[0048] In healthcare or medical facility settings, the system 100 may seamlessly incorporate information from the electronic medical record, including scores from standardized clinical assessment such as the 10-Meter Walk Test (10MWT), the Timed Up and Go Test (TUG), and the 6-Meter Walk Test (6MWT). Through applications on user devices 104 (such as smartphone applications or software downloads) and wired or wireless connectivity options such as Bluetooth, Wi-Fi, and mobile networks, the patient's sensor data can be acquired in community environments after discharge. This capability allows continuous, wireless monitoring without imposing on the patient's daily life. Sensor data can also be securely uploaded to a healthcare facility database, such as the Oracle Cerner Database (Oracle Corporation, USA), ensuring that this information is both accessible and protected as part of the patient's record. This data acquisition pipeline will be compliant with the Health Insurance Portability and Accountability Act (HIPAA), guaranteeing the utmost in patient data privacy and security. The system 100 can

also record sensor data during specified activities like walking, sitting, and standing, as well as during any generalized activities that are part of daily living (e.g., cooking, cleaning, and even engaging in hobbies or sports), as further disclosed herein.

[0049] FIG. 2 shows a process 200 which may be performed by one or more data processing devices 112 operatively coupled with the database 110 according to embodiments disclosed herein.

[0050] In step 202, the device collects historical data associated with other patients from the database. The other patients may refer to patients who are not included in the patients wearing the sensor device as shown in FIG. 1. The historical data may include one or more types of data as collected in the past, including but not limited to past sensor recordings associated with the other patients, demographics of the other patients, and the clinical outcomes associated with the other patients.

[0051] In step 204, the device trains and validates one or more predictive models based on the historical data. The models may be trained such that each model predicts a patient's future outcome, such as the projected level of functional independence, ambulation ability, and/or risk of falling, based on a predetermined type or types of input, such as the sensor data. Additionally, the models can be trained to assess whether a patient is likely to respond to the therapy, helping identify potential responders versus non-responders. The models can also be trained to provide a combined measure to describe the overall recovery. These predictions can also be viewed on an interactive dashboard (for example, a user interface or a touchscreen display on the user device 104) in different ways. For instance, the predictions as generated using the models can be illustrated as "recovery trajectories" for each patient based on current and estimated future outcomes. The predictions generated by the models can also be compared with normative data on recovery following neurological diseases or with subpopulations of interest.

[0052] In step 206, which may be an optional step in some examples, the trained models may be stored in the database to be used by the data processing device(s) and/or the user device(s) in subsequent monitoring or assessment of patient health data. For example, a data processing device may train a predictive model using the historical data such that other data processing devices or user devices may access the database to retrieve the trained model to use in the future, such that the devices

(such as those with weaker processing capabilities) may still be able to use the pre-trained model without necessarily having the capability to train such models themselves.

[0053] In step 208, the data processing device (or, in some examples, the user device prior to transmitting the new sensor data to the data processing device) extracts features from the new sensor data that is obtained from the sensor device. For example, sensor data may be processed such that the resulting signals are cleaned, filtered/smoothened, and/or mathematically transformed in preparation for extracting signal characteristics that are subsequently used in the trained model. In some examples, the signal processing can take place in real-time to ensure accurate monitoring of signal quality and computation of simple metrics. In some examples, additional operations such as data segmentation and data transformation can be executed offline immediately after the recording process (that is, the process of recording the sensor data in the database). The signal processing step may be beneficial to systematically reduce noise and convert the raw sensor data into consistent, encodable values for analysis by the trained predictive model.

[0054] In some examples, the features are mathematically extracted from the processed sensor data to characterize the signal. These features may include measurements that are clinically relevant and easily interpreted by clinicians (e.g., step velocity computed from IMUs, heart rate variability computed by ECGs and/or maximum voluntary contraction from EMGs), as well as measurements that are more abstract (e.g., mathematical moments, root-mean-square values, entropy, and/or frequency characteristics). The processed signals and extracted features can be stored in the database and accessed via the interactive digital dashboard (such as a user interface on a user device, accessible through a web browser and/or a designated application, or a combination of both) in order to allow users to review current and previous sensor measurements.

[0055] In step 210, the data processing device uses the trained predictive model(s) to assess clinical outcomes based on the extracted features. As referred to herein, the predictive model may be any suitable model using artificial intelligence, such as machine learning or deep learning, that is capable of being trained using

existing or historical data and being used to make reliable predictions on current or future events based on learning a pattern from the training data.

[0056] For example, deep learning techniques can be applied to teach a model to recognize and interpret characteristic waveforms of ECG data, or to identify a patient's sleep cycles from polysomnography data. Such applications would otherwise require time-intensive manual measurements or interpretation by trained technicians. Automatic data entry, including integration of wearable sensor measurements into patients' electronic health records, could also support the daily recording needs for treatment, insurance, and reimbursement. Reliable automation requires robust training and testing over large-scale, high-quality datasets to maximize an algorithm's generalizability to new patients or settings. In some examples, the prediction model may be an integrated prediction model including, but not limited to, multivariate regression, tree-based methods, and/or deep learning algorithms. A prediction model can be trained and/or adapted from large, labeled and/or unlabeled datasets to infer the presence and/or severity of disease and/or injuries, the time-course of functional or neuromotor recovery, response to treatment, and other outcomes for care planning, as suitable.

[0057] In some examples, predictive models, when trained on large, annotated and/or unannotated datasets, can identify the presence or severity of disease or injury by learning complex patterns in sensor data. Screening for disease using low cost, easy-to-use sensors can improve the accessibility, scope, and efficiency of current healthcare practices, especially for conditions that are mild/asymptomatic or require complex diagnostic procedures. For example, the use of wearable sensors may facilitate the early detection of infantile cerebral palsy using accelerometers or, more recently, for screening COVID-19 infections. In some examples, data from wearable sensors taken from gait therapy during the first week of inpatient rehabilitation may be used to predict a patient's functional ambulation ability at discharge, so as to help clinicians, patients, and insurance providers plan for the patient's care needs after discharge.

[0058] In some examples, sensor features can be compared to features from healthy, age-matched individuals or other patients performing the same activities. This comparison measures how "close" a patient is to their healthy or patient

counterparts for a given sensor feature, such as in average step velocity. For example, clinically relevant measurements relating to a patient's amount of motion, motion symmetry, postural sway, gait smoothness, gait regularity, step velocity, step count, muscle synergies, heart arrhythmias, and/or exercise intensity can be considered. Furthermore, the system may leverage existing normative data from literature to benchmark patient performance. For example, a patient's step velocity can be evaluated against normative data to understand their capacity and to track improvements over time.

[0059] In step 212, the data processing device transmits the clinical outcomes that are generated by the model(s) to the user device for review by the patient or by the doctor, physician, or clinician associated with the patient. The transmission of such data may be performed similarly to the transmission of the signal data, such that the user device is capable of receiving the clinical outcomes in response to the sensor data that was transmitted using the same user device. In some examples, the user device that receives the clinical outcomes may be different from the user device that transmitted the sensor data, such as when the patient's device was transmitting the sensor data but the clinician's device receives the clinical outcomes such that the clinician can review the outcomes for accuracy before allowing the patient to review.

[0060] As additional example of use, in some examples, clinicians may use sliding-scale inputs into the model to test the impact of gains or losses in any of the impairment measurements. For example, if the patient was able to improve his or her motion symmetry or muscle synergies (that is, to get "closer" to the healthy, age-matched counterparts in these domains), the clinician would be able to see an estimated impact on the patient's discharge outcomes (such as functional independence, ambulation ability, and/or risk of falling). In this way, clinicians may be able to develop and tailor rehabilitation strategies for their patients based on a data-driven approach as facilitated by the system as disclosed herein.

[0061] Optionally, in step 214, the data processing device may refine the previously trained model(s) using the new sensor data so as to improve the accuracy of future predictions performed by the same model(s). The prediction models may also be continuously updated by continuously collecting additional sensor data, for

example throughout the rehabilitation program. In some examples, step 214 may occur simultaneously with any one of the steps 208, 210, and 212. In some examples, step 214 may occur simultaneously with the database receiving the new sensor data from the patient's sensor device. As used herein, "simultaneously" may also be referred to as "real-time" or "near real-time", indicating that there is minimal time lag (for example, less than 1 minute, less than 30 seconds, less than 10 seconds, or less than 1 second, etc.) between two actions that are being performed.

[0062] In some examples, the entirety of the process 200 may be performed by a single data processing device. In some examples, the process 200 may be performed by two or more data processing devices such that each data processing device performs a different portion of the process 200 (for example, a first data processing device performs the model training and validation, while a second data processing device uses the trained and validated model to assess clinical outcomes). In some examples, a portion of the process 200 may be performed by multiple data processing devices for redundancy in order to ensure accuracy or for backups.

[0063] FIG. 3 shows a process 300 which may be performed by the user device 104 (or, in some examples, by the sensor device 102 that is capable of performing such process, such as the sensor device 102 that includes sufficient data processing capability) according to embodiments disclosed herein.

[0064] In step 302, new sensor data for a patient is continuously generated using the sensor device as explained herein. In some examples, the new sensor data is generated at a sampling rate which may be flexibly determined (e.g., via user input or determined by the clinician) so as to be tailored for the specific needs and occurring at various intervals as suitable. For example, the interval associated with the sampling rate may be every second, every minute, every 5 minutes, every 10 minutes, every 15 minutes, every 30 minutes, every 1 hour, or any other suitable interval that may be longer or shorter than is mentioned here.

[0065] In step 304, the new sensor data is transmitted or uploaded to the database of the healthcare facility data system, for example by the user device or the sensor device. The transmitting or uploading may be performed via the network 106, such that, in some examples, multiple users can simultaneously and separately upload new sensor data using the same network. In some examples, the transmitting

or uploading may be in or near real-time, or substantially instantaneous (for example, in less than 10 seconds, less than 5 seconds, less than 1 second, etc.).

[0066] In some examples, the patient may decide to take off the wearable sensor device, for example when taking a bath or entering an area where such devices are not permitted. In such cases, in step 308, the user device or the sensor device may optionally turn off or set to standby the sensor device in response to detecting detachment of the sensor device from the patient. In some examples, the sensor device may turn itself off or change its status to a standby mode when the sensor device detects such detachment. In some examples, the user device may detect the detachment and remotely control the sensor device so as to turn off or set to standby the sensor device, without having to be physically connected to the sensor device. Additionally, the user device or the sensor device may optionally turn off or set to standby the sensor device in response to detecting malfunctioning of the sensor device.

[0067] As disclosed herein, the system 100 presents a portable and adaptable solution for assessing clinical outcomes and storing clinical information and sensor data, as implemented by the processes 200 and 300 in view of FIGs. 2 and 3, as explained below. The entirety of the processes 200 and 300 may be automated such that no user input is necessary to perform the processes as disclosed herein.

[0068] Initially, either a clinician or a patient may activate the device and secure a sensor onto the patient's body. Following this setup, the patient may perform various physical activities under clinical supervision to gather specific data related to his or her performance in those activities (during which the new sensor data is continuously generated, as explained in step 302).

[0069] Subsequently, the sensor data may be uploaded to a secure database in the healthcare facility network (step 304), to further refine the machine learning model (step 214). After the completion of these movements, the system analyzes the captured data, extracting pivotal features from the movement patterns from the sensor data (step 208). The extracted features are fed into the machine learning model to assess clinical outcomes (step 210).

[0070] The outcome of the machine learning model's analysis provides a comprehensive assessment concerning the user's current clinical score, the

expected trajectory of their rehabilitation, or the efficacy of the treatment they are receiving (as transmitted for review in step 212). These assessments may be instrumental in shaping the clinical outcomes, essentially guiding the clinical decision-making process or evaluating the success of treatment interventions. Upon concluding these assessments, the user detaches the sensor, and the system is then either turned off or set to standby, awaiting its next use (step 308).

[0071] Throughout this entire process, sensor data from the sensor device may be continuously streamed to the healthcare facility's database, integrating the sensor device's functionality within the hospital network for efficient data management. This seamless integration ensures that all recorded data and generated reports are meticulously stored within the healthcare facility's database or electronic health record (EHR) system, thereby maintaining a comprehensive record for future reference or further analysis. Moreover, the iterative refinement of the machine learning model using newly collected sensor data highlights the capacity for continuous improvement of the system as a clinical tool. This not only enhances the machine learning models' accuracy and effectiveness over time but also illustrates the system's commitment to adapting and evolving in response to the dynamic nature of patient care needs. This forms a closed-loop system, from data collection through sensor technology, for quantifying and predicting relevant clinical outcomes, for refining the underlying predictive models, which exemplifies an innovative approach to patient care. Embedding this process within a healthcare facility's network infrastructure underscores a commitment to perpetual enhancement and precision in healthcare delivery, ensuring that patient care is both informed and continuously improved upon.

[0072] FIG. 4 shows an example of the components of a user device 104 and a data processing device 112 according to embodiments disclosed herein. In some examples, the components may include a processing unit 400, a memory unit 402, a user interface or display 404 for the user device 104, a network interface 406 to be operably coupled with the network 106, a sensor interface 408 for the user device 104 to be operably coupled with the sensor device 102, and a power unit 410 which may be any suitable electronics that allows the user device 104 to be turned on/off as well as to recharge the device (e.g., an on-board battery of the device). For

example, the processing unit 400 may include one or more of: central processing unit (CPU), graphics processing unit (GPU), data processing unit (DPU), system on a chip (SoC), digital signal processor (DSP), general purpose microprocessor, application specific integrated circuit (ASIC), field programmable logic array (FPGA), and/or other equivalent integrated or discrete logic circuitry as suitable. For example, the memory unit 402 may be any suitable non-transitory computer readable storage medium or media including but not limited to read-only memory (ROM), random access memory (RAM), solid state drive (SSD), flash drive, compact disc (CD), laser disc, optical disc, digital versatile disc (DVD), floppy disk, and/or Blu-ray disc, as suitable. In some examples, the memory unit 402 (non-transitory computer readable medium) may store thereon instructions or program codes (computer program instructions) which, when executed by the processing unit 400 (processor), causes the processing unit 400 to perform any one or more of the processes disclosed herein.

[0073] The user interface or display 404 may include any suitable graphical user interface (GUI) including but not limited to touchscreen displays on the user device 104 that allows the device to receive user inputs. The sensor interface 408 is any interface for the user device 104 to communicate with the sensor device 102, using any suitable wired or wireless communication protocol as known in the art. The network interface 406 facilitate secure connection with the network 106 such that communication over the network 106 is accomplished via the network interface 406 using any type of protocol, protection scheme, encoding, format, and/or packaging, as known in the art, to preserve patient data privacy and security.

[0074] In the AIP framework as implemented in the system 100, sensor data recorded during simple, targeted/everyday activities may be used to automate standardized clinical measurements, illuminate additional correlates of disease or impairment that are not typically accessible to clinicians, and predict current or future health outcomes. Importantly, these three processes can work together to form an integrated, end-to-end measurement system for evaluating patient health, as further explained herein.

[0075] FIG. 5 illustrates an embodiment of an integrated AIP framework 500 using examples in physical medicine and rehabilitation (PM&R). First, data from

sensor signals 502 are used to automatically compute traditional functional and physiological measurements for the condition of interest in the automation block 504 ("Automate" portion of AIP including, for example, gait speed, balance score, and/or ectopic beats), so as to ease the burden on clinicians who would otherwise be manually scoring, computing, and recording such measurements. Concurrently, data from the sensor signals 502 capture additional measurements relating to health and impairment, as per the illumination block 506 ("Illuminate" portion of AIP including, for example, joint angles, spatiotemporal kinematics, muscle coactivation, and/or postural sway), that are not available in standard clinical practice.

[0076] The features generated by the automate and illuminate processes in blocks 504 and 506 can be combined with other sensor data, as well as patient descriptors (e.g., demographics, co-morbidities, past clinical outcomes, and/or medical history) as included in patient characteristics 508 to form a broad set of features 510. These features are then input into a machine learning model 512 to infer a patient's current or future outcomes as per the prediction block 514 ("Predict" portion of AIP including, for example, disease diagnosis, potential recovery trajectory, potential response to treatment, and/or potential discharge location). It is to be understood that the AIP framework 500 may be modular such that these processes may work individually or in combination to compute a target outcome.

[0077] Wearable sensors as implemented in the AIP framework 500 can easily automate data capture and scoring for standardized clinical measurements, thereby easing clinician burden, increasing efficiency, eliminating inter- and intra-rater reliability, and enabling more frequent (or even continuous) evaluation as needed for granular patient monitoring. Automated measurement by wearable sensors can also be extended to telemedicine for remote evaluation (such as at home and in the community) as needed. In rehabilitation, standardized clinical outcome measurements allow therapists, physicians, and insurance providers to track patient function, evaluate treatment efficacy, and reimburse services provided.

[0078] As such, the AIP framework 500 facilitates an all-inclusive, modular paradigm for utilizing sensor-based measurement in healthcare using the processes of automation, illumination, and prediction. These processes can be used independently or in combination to evaluate patient health using objective, high-

resolution measurements from wearable sensors. A scenario in physical rehabilitation is depicted in FIG. 5, as explained above. First, sensor data 502 is recorded during specific activities or clinical tests of interest. Such data 502 (or features extracted from the data) is inputted into an automation block 504 for the automatic, digital scoring of traditional clinical measurements such as gait and balance function or cardiac event detection, using signal processing and/or artificial intelligence. The same data can be processed to form illumination measurements in the illumination block 506 of underlying impairment that are not readily available in traditional rehabilitation settings, such as detailed gait kinematics or muscle activation patterns. For example, Table 1 lists common measurements taken during stroke rehabilitation, including how they are traditionally scored and how they might be automated using wearable sensor data. Specifically, measurements with great complexity, high inter- and intra-rater variability, and/or meaningful care implications are optimal candidates for automation.

Table 1. Automatically scoring post-stroke clinical measurements from sensor data

Clinical Outcome	**Tests**	**Measure-ment**	**Traditional Scoring**	**Sensor Scoring**	
				Example Sensor Types	***Automation Approaches***
Walking speed	10-Meter Walk Test	Time to walk a known distance (m/s)	Stopwatch	ACC, GYR	• Human Gait Models • Direct Integration • ML
Walking endurance	6-Minute Walk Test	Distance walked over a known time (m)	Distance wheel	ACC, GYR	Accumulated step/stride length from: • Human Gait Models • Linear approximation • Direct integration • Neural networks
Sensori-motor impairment	Fugl-Meyer Assessment	Score (0-2) per item	Trained therapist	ACC, GYR, Pressure	ML
Muscle spasticity	Modified Ashworth Scale	Score (0-4) per item	Trained Therapist	EMG, ACC; Force, Angle	ML

Balance	Berg Balance Scale	Score (0-4) per item	Trained Therapist	ACC	ML
Heart rhythms	Electro-cardio-graphy	Cardiac event detection	ECG paper strip; digital calipers	ECG	• Rule-based morphological classification • ML

ACC = Accelerometer; GYR = Gyroscope; EMG = Electromyography;
ECG = Electrocardiography; ML = Machine Learning

[0079] Furthermore, wearable sensors can provide high-resolution measurements of body function and impairments that are not usually quantified in the inpatient/outpatient/home settings. Illuminative measurements such as kinematic movement patterns, muscle synergies, cardiovascular response, and brain activity (i.e., from inertial, electromyographic, electrocardiographic, and electroencephalographic signals, respectively) during everyday activities or specific clinical tests, may improve clinician's understanding of underlying impairments, compensatory strategies, or risk of adverse events. Similarly, physical activity measurements recorded from sensors can track a patient's adherence to exercise guidelines or changes in movement quality. If clinicians can easily obtain these illuminative measurements, they can attend to deficits and evaluate disease progression/recovery more frequently and more precisely compared to using observational tests or patient reports alone.

[0080] In PM&R, meaningful illuminative measurements may include spatiotemporal walking patterns, muscle synergies, joint motion, postural stability, or upper limb use. Due to the complex nature of human movement, true recovery is not likely to be captured by any single parameter or measurement domain. Multidimensional measurements may be needed to fully evaluate recovery and to separate primary pathology from a compensatory or adaptive strategy. For example, inertial sensors may be used to monitor changes in gait quality (i.e., asymmetry of spatiotemporal and kinematic parameters) during early-stage stroke recovery. Despite improvements in gait speed and spatiotemporal symmetry, patients may exhibit significant asymmetries in joint range of motion and limb kinematics. As such "amount of motion" (AoM) may be proposed as a useful metric of therapy dosage, computed from gyroscope signals placed on the lower limbs and pelvis. AoM may

be a stronger predictor of gait recovery than step count or exercise intensity. Other illuminative measurements may be considered to assess patient function and inform treatment as suitable.

[0081] As another example, potential value of illuminative measurements in the Timed Up and Go (TUG), a test which evaluates gait mobility and is strongly correlated with other functional outcomes, may be considered. The traditional TUG score is the total time required to perform a sequence of actions, including standing, walking, turning, and sitting, as shown in FIG. 6.

[0082] FIG. 6 shows a graph 600 where filled/colored circles 602 represent sensor-based measurements from a 57-year-old patient with left-side hemiparesis during the TUG clinical test, normalized by the average value across similarly aged nondisabled controls (such that 0 on the y-axis indicates the mean value of 10 controls aged 50-59 years). Gray bars 604 represent standard deviation of the controls. Darkness of shading or color of the circles indicates relative distance from the gray bar (lighter shading or color (e.g., green) if patient was within the standard deviation of controls, transitioning to darker shading or color (e.g., red) for the measure farthest away from the boundary of the gray bar). Compared with the traditional measure (total TUG duration), the sensor provides a more complete picture of the patient's differences compared to nondisabled controls, which can inform specific rehabilitation strategies and track progress with greater resolution. Sensor measurements were derived from an accelerometer placed on the lower back. "Fwd" stands for "forward"; "US" stands for "unaffected side"; "AS" stands for "affected side"; "CoM Δh" stands for "change in height of the center of mass during walking".

[0083] FIG. 6 illustrates how sensor data provides detailed information about a patient's performance during each action relative to similarly-aged nondisabled controls. Compared to controls, this patient exhibited reduced step length on the affected side, likely explaining the greater number of steps taken. Additionally, the patient had a slower walking speed, prolonged time for turns, and uncontrolled descent when sitting down (indicated by the reduced range of the patient's forward pitch or "Fwd Pitch" and shorter stand-to-sit duration or "Duration"). Taken together, such data can inform appropriate interventions that emphasize posture and gait

training with changes of direction and longer steps, as well as eccentric control during stand-to-sit transitions. In contrast, the traditional TUG score 606 alone cannot provide such details to a clinician who is unfamiliar with the patient.

[0084] FIG. 7 shows a graph 700 illustrating how, in addition to predicting the current health state, biophysical sensor data can be used to predict future outcomes, such as risk of developing disease or post-diagnostic recovery prospects. Sensor data collected early in a treatment program can be combined with a predictive model to map a patient's recovery trajectory 702. This allows clinicians to estimate the treatment effect relative to a known standard-of-care curve 704 and adjust treatment accordingly to optimize the target outcome. It is postulated that sensor data recorded in the early stages of treatment can be used to compute a patient's recovery trajectory curve 702, allowing clinicians to estimate the effect of the treatment on future outcomes as compared to a curve 704 representing the standard of care. Predicting a patient's response to treatment and identifying the underlying factors contributing to their response or non-response enables more optimized care plans, to minimize the cost of intervention and develop new, personalized interventions to maximize recovery.

[0085] In PM&R, validated predictive models can contribute to precision medicine by helping healthcare professionals create tailored, patient-specific therapy programs and identify expected discharge needs (e.g., skilled care, medical equipment, or home modifications). To date, most models use only demographic, clinical, and neurological variables collected to predict functional outcome. However, it has been demonstrated that combining clinical data (collected at healthcare facility admission) with inertial sensor data (collected during a mid-stay ambulatory task) provided superior prediction of the discharge Functional Independence Measure compared to clinical data alone. Similarly, models using sensor data recorded early in the stroke rehabilitation process were observed to perform almost 30% better than models using clinical data alone when predicting a patient's future outcomes.

[0086] Currently, wearable sensor technology is unique in its ability to monitor biophysical data continuously, irrespective of environment. The AIP processes can be implemented not only in the presence of a practitioner (e.g., in the lab or clinic) but also when the patient is unsupervised (e.g., in a hospital room, home, or

community). This is of particular interest given the mounting evidence that environmental factors affect performance, for example, with patients performing differently at home than in a lab. The desired use case of AIP should be further considered, such as whether the sensor data will be obtained from brief, controlled patient activities or on longer-term, free-living data.

[0087] Beneficially, sensor-based monitoring of at-risk populations facilitates detection of diseases earlier and more accurately than ever before. It also enables the tracking of patient-specific symptom progression. In turn, this can facilitate early intervention, personalized treatment, and, ultimately, the extension of care from the clinic to the home and community. Special attention should be given to training and validating AIP models for patient applications since global models or models trained on data from non-impaired populations may not perform as well for patients; impairment- or patient-specific models may be needed to achieve sufficient performance. For individuals in rural settings, sensor-based measurements recorded in the home and community can also be used to support telehealth and reduce the burden of travelling to in-person appointments. This is especially timely given the expansion of virtual care services that arose during the COVID-19 pandemic.

[0088] Additional advantages for implementing the systems and models as disclosed herein are explained. Rehabilitation systems commonly favor a one-size-fits-all approach, offering patients uniform therapy structures and dosages based on prevailing evidence and nationwide insurance reimbursement models. This approach is necessitated by the lack of objective evidence and wide range of motor impairments that make it difficult to establish quantifiable prognosis or personalized recovery predictions. The current monitoring, treatment, and evaluation of patients rely on infrequent clinical assessments, performance-based rehabilitation measurements, and patient self-reports. Performance-based rehabilitation measurements are limited by lack of sensitivity, reliability, and validity in identifying changes or clinical efficacy of treatment or recovery progression. The quality of patient-reported recovery is limited by recall and rater bias. Thus, there exists a compelling need for objective, reliable, and continuous monitoring of patients to assist clinicians and therapists in making informed decisions about personalized

treatment and recovery. The adoption of the systems as disclosed herein will provide several advantages compared to alternative methods in the field as explained below.

[0089] Firstly, the systems disclosed herein would enable a more objective and data-driven approach to treatment, leveraging information from the wearable sensors and validated prediction algorithms. It is expected that the personalized "recovery signatures" found within the data can assist clinicians and therapists to monitor and treat patients in an unbiased manner using high-resolution metrics, without the need to rely on subjective assessments. This approach is expected to help a patient's care team to determine the effectiveness of treatment, direct subsequent treatment, assess readiness for discharge from the healthcare facility, and plan for discharge needs (e.g., level of care, functional independence, and need for assistive devices, orthotics). The system's implementation could reduce healthcare costs by guiding efficient resource usage and preventing later health complications via early intervention.

[0090] Secondly, the systems disclosed herein would also facilitate continuous monitoring and long-term follow-up. This is required to better understand recovery progression, from the early stages of recovery until a plateau in therapy-based performance, as well as community mobility remote monitoring after discharge. This approach would reduce the need for frequent in-person visits to assess patient function and impairment. Understanding the recovery progression for different severities of patient impairment will provide insight into the optimal timing to intervene therapeutically and/or pharmacologically, and which experimental interventions are successful. Continuous, sensor-based monitoring inside and outside of the clinic can also be used to identify biomarkers of long-term recovery and community mobility, which in turn can guide the design of personalized teletherapies and interventions following discharge from the healthcare facility.

[0091] Commercial applications for the systems as disclosed herein include applications in commercial areas across various healthcare settings. The implementation of the systems disclosed herein is especially beneficial in large medical facilities such as hospitals, where each floor can be equipped with one or more systems. Such integration allows clinicians to effortlessly assess clinical outcomes using the system. As patients undergo rehabilitation, their progress data,

captured by the wearable sensors, are automatically synchronized with the hospital's central database for medical records. This feature streamlines the data management process, ensuring that patient information is updated in real-time, accessible, and securely protected. In clinics and rehabilitation centers, the systems as disclosed herein can serve as a crucial tool for continuous patient monitoring, providing clinicians with detailed insights into each patient's recovery journey. The system's flexibility to adapt to different neurological disorders, such as stroke, multiple sclerosis, Parkinson's disease, cerebral palsy, and other movement disorders, makes the system a versatile solution for a wide range of rehabilitation needs. Furthermore, individuals with neurological or movement disorders and those interested in proactive health monitoring represent a potential consumer market. Direct-to-consumer marketing strategies, including partnerships with wearable device distributors, can facilitate widespread adoption among individuals seeking innovative solutions for self-monitoring and health improvement.

[0092] The AIP framework for integrating wearable sensors in healthcare applications and everyday clinical care may provide comprehensive, data-driven insights about disease progression and recovery, empowering clinicians to design targeted interventions for their patients' specific needs. In this way, sensor technology may be leveraged to significantly expand the capabilities of our current healthcare system. Further, although the use of body-worn sensor technology is described herein, the AIP framework is equally applicable to sensor-integrated environments (e.g., smart homes). AIP can also be applied to data from other sources, such as human pose estimates from video recordings or radio waves in the rising field of computer vision.

[0093] Various modifications and additions can be made to the exemplary embodiments discussed without departing from the scope of the present disclosure. For example, while the embodiments described above refer to particular features, the scope of this disclosure also includes embodiments having different combinations of features and embodiments that do not include all of the described features. Accordingly, the scope of the present disclosure is intended to embrace all such alternatives, modifications, and variations as fall within the scope of the claims, together with all equivalents thereof.

CLAIMS

What is claimed is:

1. A system for continuous monitoring and assessment of patient health, the system comprising:

at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate new sensor data associated with the patient; and

a data system comprising a database and at least one data processing device, wherein the data processing device is configured to:

collect historical data associated with other patients from the database;

train and validate at least one predictive model based on the historical data;

extract features from the new sensor data received from the sensor device;

assess, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and

transmit the clinical outcomes to be reviewed by the patient or a clinician of the patient.

2. The system of claim 1, wherein the data processing device is further configured to refine the trained and validated model using the new sensor data.

3. The system of claim 1 or 2, further comprising at least one user device operatively coupled with the sensor device, the user device configured to receive the new sensor data from the sensor device and transmit the new sensor data to the data processing device.

4. The system of claim 3, wherein the user device is further configured to receive the clinical outcomes from the data processing device and display the clinical outcomes to be reviewed by the patient or the clinician.

5. The system of claim 3 or 4, wherein the user device is further configured to turn off or set to standby the sensor device in response to detecting detachment of the sensor device from the patient.

6. The system of claim 3 or 4, wherein the user device is further configured to turn off or set to standby the sensor device in response to detecting malfunctioning of the sensor device.

7. The system of any one of claims 1-6, wherein the new sensor data includes one or more types of biometric or activity data.

8. The system of claim 7, wherein the biometric or activity data includes one or more of: motion data from one or more inertial measurement units (IMUs), muscle activity data from electromyography (EMG), heart activity data from electrocardiography (ECG), or physiological signal data from photoplethysmography (PPG).

9. The system of claim 7, wherein the extracted features include one or more of: a step velocity obtained from the IMUs, a heart rate variability obtained from the ECG, or a maximum voluntary contraction obtained from the EMG.

10. The system of any one of claims 7-9, wherein the new sensor data further includes one or more contextual information associated with an environment in which the patient is located.

11. The system of any one of claims 7-9, wherein the new sensor data is generated at a sampling rate that is adjustable based on user input.

12. The system of any one of claims 1-11, wherein the data processing device is configured to extract the features from the new sensor data received from the sensor device by:

processing the new sensor data in or near real-time to reduce noise from the new sensor data, and

extracting the features from the processed sensor data.

13. The system of claim 12, wherein the data processing device is further configured to perform data segmentation and data transformation offline in response to recording the new sensor data in the database.

14. The system of any one of claims 1-13, wherein the extracted features include one or more of: mathematical moments, root-mean-square values, entropy, or frequency characteristics that are associated with the patient.

15. The system of any one of claims 1-14, wherein the at least one predictive model is trained using sensor recordings, demographics, and clinical outcomes that are associated with the historical data.

16. The system of any one of claims 1-15, wherein the clinical outcomes associated with the patient include one or more of: projected level of functional independence for the patient, predicted ambulation ability of the patient, predicted risk of falling for the patient, or predicted overall recovery or recovery trajectories for the patient.

17. A method for continuously monitoring and assessing patient health, the method comprising:

collecting historical data associated with other patients from a database;

training and validating at least one predictive model based on the historical data;

extracting features from new sensor data received from at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate the new sensor data associated with the patient;

assessing, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and

transmitting the clinical outcomes to be reviewed by the patient or a clinician of the patient.

18. A non-transitory computer readable medium storing computer program instructions that, when executed by a processor, cause the processor to:

collect historical data associated with other patients from a database;

train and validate at least one predictive model based on the historical data;

extract features from new sensor data received from at least one wearable sensor device attached noninvasively to a patient, the sensor device configured to continuously generate the new sensor data associated with the patient;

assess, using the trained and validated model, clinical outcomes associated with the patient based on the extracted features; and

transmit the clinical outcomes to be reviewed by the patient or a clinician of the patient.