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A Digital Ecosystem of Diabetes Data and Technology: Services, Systems, and Tools Enabled by Wearables, Sensors, and Apps

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Abstract

The management of type 1 diabetes (T1D) ideally involves regimented measurement of various health signals; constant interpretation of diverse kinds of data; and consistent cohesion between patients, caregivers, and health care professionals (HCPs). In the context of myriad factors that influence blood glucose dynamics for each individual patient (eg, medication, activity, diet, stress, sleep quality, hormones, environment), such coordination of self-management and clinical care is a great challenge, amplified by the routine unavailability of many types of data thought to be useful in diabetes decision-making. While much remains to be understood about the physiology of diabetes and blood glucose dynamics at the level of the individual, recent and emerging medical and consumer technologies are helping the diabetes community to take great strides toward truly personalized, real-time, data-driven management of this chronic disease. This review describes "connected" technologies—such as smartphone apps, and wearable devices and sensors—which comprise part of a new digital ecosystem of data-driven tools that can link patients and their care teams for precision management of diabetes. These connected technologies are rich sources of physiologic, behavioral, and contextual data that can be integrated and analyzed in "the cloud" for research into personal models of glycemic dynamics, and employed in a multitude of applications for mobile health (mHealth) and telemedicine in diabetes care.

Keywords

apps, connected devices, data, ecosystem, sensors, wearables

Imagine a day in the future when a person with diabetes arrives at a restaurant that she is visiting for the first time. As she is being seated, her smartwatch displays several recommended menu items alongside suggested insulin dosing strategies and predicted postprandial glycemic responses. This automated guidance is based on real-time and historic data from her diabetes devices and health records, biometric readings from sensors in her clothing, and data from her smartphone; and personalized to her health and lifestyle goals that she recently set in consultation with her physician. How far in the future will this scenario be commonplace? Perhaps not as far as one might think—most of the elements already exist in some form, and current and emerging technologies are beginning to coalesce as a "digital ecosystem" in the diabetes management space. Similar to a biological ecosystem, defined as "a biological community of interacting organisms and their physical environment," the digital ecosystem of diabetes management involves hardware and software capable of collecting, transmitting, displaying, and interpreting data about the physiology, behavior, and environment of the individual with diabetes. Vital to this digital ecosystem are the pathways by which data enter it and the sources of the data, which are the focus of this review.

The rapidly growing number of connected consumer technologies has given rise to the so-called Internet of things (IoT), defined by the International Telecommunication Union as "a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies."[1] In principle, every "thing" in the physical world can be equipped with electronics and software that enable connectivity to the internet, and hence data can flow continuously between embedded systems/sensors and remote computers/servers/controllers. The connected thing itself, while executing its intended function, may automatically report data (including measurements, performance, and status) to a remote computer where the data can be archived and interpreted, and then updated instructions, features, and functions may be deployed from the computer back to the connected thing. A popular example in the consumer

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domain is the Nest Learning Thermostat,[2] a Wi-Fi-enabled temperature control device for homes and businesses which can be programmed and controlled by the owner from a smartphone app or a website, and remotely updated by the vendor when new software and firmware are available. Connected things are emerging in many other products in the consumer and industry domains,[3,4] and leverage an ever expanding global capacity for "cloud computing," defined as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (eg, networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction."[5]

Now, connected devices have entered the health and wellness space, hatching the Healthcare IoT. It is suggested that digital health, including connected things, can "revolutionize the healthcare industry by making diagnosis, treatment, and prevention widely accessible at a fraction of current costs," with great impact in particular on management of chronic diseases including diabetes.[6] Connected glucometers, for example, are available as physical attachments to smartphones,[7] devices paired with smartphones via Bluetooth,[8-10] and stand-alone devices with a dedicated cellular connection,[11,12] complemented by devices designed to wirelessly sync data from many nonconnected glucometers.[13] More recently, the first smartphone-connected continuous glucose monitor (CGM) was introduced,[14] and additional connected diabetes devices are soon to follow, including insulin pumps and pens.[15-19] Data from connected diabetes devices can be collected and combined with data from other sources for many applications in both self-management and clinical care.[20]

Of course, diabetes management is about more than blood glucose readings and insulin doses—a host of factors influence glycemia, and impact each individual with diabetes differently. Data for many of these factors are increasingly available from a variety of technologies designed for consumer use, and as they enter the diabetes digital ecosystem more pervasively, they may be employed to deepen our understanding of diabetes at the level of the individual, and hence enable truly personalized diabetes care.

There's an App for That

With nearly ubiquitous cellular and Wi-Fi connections to the internet and ever increasing processing capability, the smartphone now serves as a powerful mobile computing platform with rich data collection capacity not only through its built-in sensors but also by virtue of software in the form of native applications, or "apps." As of October 2014, 64% of American adults owned a smartphone,[21] and millions of apps are currently available for consumers to download for a variety of purposes including gaming, shopping, and social media.[22] Apps for mobile health (mHealth) have proliferated in recent years—more than 165,000 health and wellness apps are now offered in online marketplaces.[23,24] Independent efforts have been made to curate an mHealth app repository and database,[25] and the Ochsner Health System (New Orleans, LA) even maintains a center for in-person learning about health and wellness apps.[26] There are many hundreds of diabetes mHealth apps (extensively reviewed elsewhere),[27-31] and many thousands of apps for tracking various types of "nondiabetes" data that are relevant to diabetes management, including exercise, sleep, stress and mood, menstrual cycle, diet, medications, and more. The regulatory environment has evolved to accommodate these apps, including the publication of FDA guidance for mobile medical apps,[32] though concerns persist as to their safety and efficacy in diabetes management.

While most apps for diabetes management involve manual logging of blood glucose and insulin data (ie, serving as digital equivalents of the more burdensome and error-prone paper journals of old), some apps feature games, challenges, and social and educational content to incentivize users to keep up with data entry, for example the various apps from mySugr (mySugr GmbH, Vienna, Austria), Sugar Streak (Streak Inc, San Diego, CA), and OneDrop (Informed Data Systems Inc, Austin, TX). As decision making and data tracking in diabetes management already constitute a substantial burden on the individual with diabetes, apps that prove successful over the longer term are likely to combine such interactive incentives with more passive means of data collection (including integration of data from connected diabetes devices with complementary data from built-in smartphone sensors and wearables—currently 10% of mHealth apps can link to a sensor or device[24]) and personalized, context-aware feedback powered by analytics running on the smartphone or in the cloud, delivered to the user via the smartphone itself or another display interface, such as a wearable technology.

Wearables Aren't Just for the Wrist

The era of smart, connected wrist-worn technology has arrived, with a plethora of options available to the consumer from the likes of Apple, FitBit, Garmin, Google, Intel, Jawbone, Microsoft, Misfit, Pebble Technologies, Polar, Samsung, and many others. Frequently referred to as "wearables," these sensor-packed devices range from simple activity trackers to feature-rich smartwatches, and typically include capabilities for both collecting and displaying many types of data (eg, steps taken, heart rate, sleep, location). The wrist-worn wearable is usually complemented by companion smartphone apps and/or computer software for more sophisticated data analysis and visualization, often in connection with cloud storage and computing on the collected data. The glanceability of the wrist-worn display is notable for the convenience and discretion it offers to the person with diabetes, for example reducing the need to frequently retrieve a medical device from a pocket or purse to view a glucose reading.[33]

While much attention is focused on the current and emerging crop of smartwatches and wrist-worn fitness trackers, a new generation of smart garments (eg, shirts,[34-36] socks,[37] and underwear[38,39]) is also entering the market, building on years of academic research on textile-based sensing and smart garment design.[40-42] Incorporating smart fabric sensor and electronic textile technologies to passively collect data on a host of important physiological and behavioral factors, such smart garments have applications in sports, defense, and public safety, and even iconic fashion brands have entered the smart garment space.[43] Adoption of smart garments may be commonplace in the near future, including for people with diabetes, providing a source of rich biometric data that unobtrusively fits individual preferences and lifestyles.

Even closer to the body than clothing are sensors that adhere directly to the skin, for example single-lead electrocardiogram (ECG) patches that continuously record heart rhythm data and can, in some cases, outperform the traditional Holter monitor in detecting arrhythmias at a fraction of the cost.[44] While some such devices still require post hoc data analysis (ie, the data are retrieved following temporary or episodic usage of the device), new skin-adherent biometric sensing modalities are being developed in increasingly smaller and more flexible form factors, and leveraging advances in low-power computing and networking to continuously sense and transmit a variety of physiologic parameters[45-48] that could be analyzed in near real-time on a smartphone or in the cloud. Even the eye presents real estate for sensing, as companies like Google and Novartis team up to develop and commercialize contact lenses capable of detecting analytes present in tears,[49] and sensor-loaded smartglasses are likely to stay in the game, as well.[50]

While wrist-worn wearables are in the spotlight today, the garment-integrated and body-worn sensors of tomorrow will provide many additional channels of multidimensional continuous data through increasingly seamless integrations of technology, fashion, and lifestyle. These data may be employed to tailor an individual's diabetes treatment regimen around his personal exercise habits, stress triggers, and circadian rhythms, even as they change throughout the individual's life.

Location, Location, Location

Once the domain of dedicated GPS devices, geolocation technology is now widespread in consumer devices like smartphones and wearables, enabling a variety of services from location-aware restaurant recommendations to mapping hikes and outdoor workouts. In the diabetes context, studies have evaluated the relationship between location (eg, home versus work) and glycemia,[51,52] and open-source tools, such as GlucoMap, have been developed to enable the display of continuous glucose and physiologic data in geographical context.[53] Knowledge of an individual's time-stamped location enables the retrieval of a host of other data types linked to geography, including elevation, temperature, sunlight/UV exposure, air quality, urban versus rural, proximity to businesses or clinical facilities, and more. Access to such integrated data may finally enable researchers to quantitatively measure the impact of geospatial and environmental variables on glycemia, providing new dimensions of understanding for individual diabetes management. Beyond research, the integration of glucose and location data has applications in patient health and safety, including emergency services.[54]

The Meal Challenge

Information about meals is particularly important to diabetes management, yet these data are problematic to obtain. Active dietary self-monitoring, such as paper-based or app-enabled food journaling, is burdensome for the individual to maintain and labor-intensive for the HCP to review, and thus sustained adherence is poor. From an analytics perspective, carbohydrate intake may be approximated post hoc from data manually entered into a bolus calculator (eg, on an insulin pump or glucometer, or within an app), though the difficulty of accurately counting carbs can render these data unreliable, and incomplete in the sense that other macronutrient content (eg, fat or protein) is typically not accounted for. If these devices are connected, some analytical value may be realized by inferring eating moments from the time-stamps of insulin bolus data, though not every bolus is administered to cover food intake, likely leading to false positive calls of meal events and diminishing confidence in any therapeutic insights gained from these data.

Recognizing the usefulness of passively tracking eating moments (ie, with little or no burden on the user), ongoing research is developing methods to detect an individual's consumption of meals and snacks via data from sensors embedded in wearable technologies, most recently including a smartwatch,[55] smartglasses,[56] or an earpiece.[57] Using machine learning techniques to analyze the continuous time-series sensor data, these approaches are increasingly accurate in distinguishing true eating moments throughout an individual's daily activity, and hold great potential for passively tracking meal and snack events, as the technologies mature toward commercialization.

In the meantime, people with diabetes have options for actively logging meals beyond entering carbs into a device or a smartphone app, such as capturing images with a smartphone or wearable camera.[58,59] For example, the Meal Memory app (Databetes Inc, Brooklyn, NY) provides a simple procedure for capturing meal images using the smartphone camera, with the additional capability of passively integrating blood glucose data that are collected to the user's smartphone.[60] Other smartphone apps also include photo-based meal logging, and looking beyond meal images as a simple visual record, research is ongoing toward automated annotation of meal content from photos.[61,62] Someday, individuals may even carry miniaturized spectroscopy-based devices capable of quantitatively characterizing the content of everything they eat.[63,64]

Meal information collected by these tools, if sufficiently accurate, could be employed by a next-generation bolus calculator (in this case, the burden of active meal-tracking with a camera or other device may be offset by alleviation of the mental math and guesswork currently associated with determining an insulin dose) or by a closed-loop artificial pancreas system to enhance the proactive delivery of insulin at meal times. Even a visual record of nutrition habits is useful in reviewing and refining diabetes management strategies.

Consumption and Synthesis of Data for Information, Insight, and Action

For years, data collected by diabetes devices (and other devices, for that matter) have been difficult to make full use of, requiring specialized (usually vendor-specific) hardware and software to retrieve and visualize the data.[65] This challenge has been tackled in the diabetes space by companies developing device-agnostic platforms for data retrieval, analysis, and transmission,[66-68] and now the trend toward device connectivity offers an unprecedented opportunity for diabetes data to be more thoroughly utilized for applications in patient self-management and clinical care, independently or joined with data from other sources such as described above. For example, the HealthKit utility on Apple's mobile operating system (iOS) allows a user to share data between mHealth apps on her iPhone,[69] enabling data from her connected CGM to be integrated with other apps (eg, meal-tracking[70]) and even directly into an electronic medical record (EMR) system.[71]

The fitness tracking device industry provides useful precedent for how data in the cloud can be accessed in a standardized fashion, typically via an application programming interface (API) accompanied by documentation and even software developer kits (SDKs) for use by third-party software developers.[72-75] By making the data more systematically portable, APIs enable consumption of data into tools and services that integrate diverse data for visualization and analysis by individuals[76,77] and enterprise,[78-80] including health care providers and payors. As the diabetes industry follows suit with connected devices and APIs, increased data availability will enable the "big data" approach to revolutionizing diabetes management,[81] helping to address some acknowledged gaps in the application of information technology to diabetes care including EMR integrations and decision support capabilities,[82] such as data-driven adjustments to an individual's insulin doses[83,84] and automated pattern recognition of problematic glucose trends.[85]

To date, the development of artificial pancreas (AP) technology has been one of the major drivers for integrating data to improve diabetes management, as years of research and inpatient studies have recently progressed to numerous outpatient studies of systems wherein patients' blood glucose levels are under automated closed-loop control via glycemia-responsive delivery of insulin or insulin and glucagon.[86,87] Connected consumer devices play a role in the expansion of this work, for example the use of a smartphone as a hub for a "mobile medical network," serving as both the computing platform for AP algorithms (wirelessly receiving CGM data and controlling hormone delivery) and the user interface (UI) for the patient,[88,89] and the smartphone's inherent connectivity to the cloud facilitates the monitoring of AP study participants as part of a telemedicine infrastructure.[90-92] As such, a smartphone-based, cloud-connected AP system may be augmented by data from many of the sources noted previously, both to better understand influencers of glycemia in real world settings, and to drive the adaptation of more individualized AP control algorithms.

While issues of device interoperability[93] and data standards[94] are yet to be fully resolved, and data privacy and security will require constant vigilance,[95,96] today one can readily envision precision diabetes management driven by robust data collection, synthesis, and analysis (retrospective and real-time), with context-aware individualized guidance presented to the patient and caregivers in a coordinated fashion. A person with diabetes may receive personalized meal and insulin recommendations as in the aforementioned scenario. Furthermore, her spouse may be automatically notified several hours later that her postprandial glycemia was in-range, and may send her a congratulatory text message. In addition, her endocrinologist may receive regular reports including her detailed diet and exercise information alongside all of her diabetes device data, accompanied by a narrative of patterns identified in the data by specialized analytics as well as algorithm-based suggestions for changes to her treatment regimen to optimize her glucose control—without waiting months for an in-person visit at the clinic. All the while, the person with diabetes may elect to have her data anonymized and made available to researchers developing the next generation of personalized closed-loop AP technologies and other precision medicine innovations leveraging unprecedented, massively parallel n-of-1 data sets.[97] To achieve this vision, a collaborative approach is needed: researchers must continue their efforts to understand blood glucose dynamics and diabetes management at the level of the individual, industry must design secure connected products with interoperability and personalization as basic features, and regulatory bodies must accommodate the inclusion of diverse consumer and enterprise technologies that will benefit people with diabetes and their caregivers. The realization of this digital ecosystem of tools for diabetes care is underpinned by the current trends toward device connectivity and data openness, which hold great promise to reduce the burdens of diabetes for individuals, caregivers, and society.

Abbreviations

AP, artificial pancreas; API, application programming interface; ECG, electrocardiogram; EMR, electronic medical record; FDA, US Food and Drug Administration; GPS, global positioning system; HCP, health care professional; IoT, Internet of things; mHealth, mobile health; SDK, software developer kit; T1D, type 1 diabetes; UI, user interface

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