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Diabetes and hypertension MobileHealth systems: a review of general challenges and advancements

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Abstract

Mobile health (mHealth) systems are sipping into more and more healthcare functions with self-management being the foremost modus operandi. However, there has been challenges. This study explores challenges with mHealth self-management of diabetes and hypertension, two of the most comorbid chronic diseases. Existing literature present the challenges in fragments, certain subsets of the challenges at a time. Nevertheless, feedback from patient/users in extant literature depict very variegated concerns that are also interdependent. This work pursues provision of an encyclopedic, but not redundant, view of the challenges with mHealth systems for self-management of diabetes and hypertension.

Furthermore, the work identifies machine learning (ML) and self-management approaches as potential drivers of potency of diabetes and hypertension mobile health systems. The nexus between ML and diabetes and hypertension mHealth systems was found to be under-explored. For ML contributions to management of diabetes, we found that machine learning has been applied most to diabetes prediction followed by diagnosis, with therapy in distant third. For diabetes therapy research, only physical and dietary therapy were emphasized in reviewed literature. The four most considered performance metrics were accuracy, ROC-AUC, sensitivity, and specificity. Random forest was the best performing algorithm across all metrics, for all purposes covered in the literature. For hypertension, in descending order, hypertension prediction, prediction of risk factors, and prediction of prehypertension were most considered areas of hypertension management witnessing application of machine learning. SVM averaged best ML algorithm in accuracy and sensitivity, while random forest averaged best performing in specificity and ROC-AUC.

Keywords: MobileHealth, Diabetes, Hypertension, Smartphone, Prescription adherence, Security, Machine learning

Introduction

The number of people needing healthcare and number of caregivers are growing disproportionately, with the later lagging. It is not just because of world population increase, but as observed by Anderson et al. [1], healthcare-consumers are living longer. As mobile phone technology has become indispensable, the number of users has increased substantially on a yearly basis; researchers and medical practitioners are taking advantage of the abilities of mobile phone technology for the interest of the medical sector. Though many years have passed and there has been respectable advancements in mobile system intervention in health, mobile health care is still considered a developing sector in health telematics [2, 3] yet to attain its projected heights [4].

Mobile health care is the use of mobile phones technology to facilitate health care demands, thereby making it easily available and cost effective [5]. Mobile wireless technology has the capability to innovate the manner in which people interconnect with the public health services [6]. With it, health records can be shared remotely between healthcare workers and medical specialist for discourse with the purpose of reducing time and cost for patients and health specialists and effectively administering treatment for people with long-term illness [7]. Diabetes mellitus and hypertension are two comorbid chronic diseases with rising prevalence globally, which will be considered in this work.

Overview of diabetes mHealth system

Significant improvements have been apparent in diabetes technologies (DTs), which have aided accessible, customizable, and personalized caregiving. One way of supporting patients in self-care and self-management is through the use of technology [8]. Examples of DTs include continuous subcutaneous insulin infusion (CSII), continuous glucose monitoring (CGM), or an amalgamation of both devices called automated insulin delivery (AID) [9]. Both CSII and CGM devices have proven useful in glycemic control in both ambulatory and hospitalized diabetic patients [10]. Further example of diabetes technology is a health software deployed on handheld devices, which has presented an improved approach to management of diabetes. Figure 1 presents the typical components of an mHealth system for diabetes (both human and gadgets) and how they work together. As shown in Fig. 1, such apps feature the following: blood glucose level (BGL) tracking, insulin usage tracking and dosage calibration, diet and physical activities monitoring, and measuring and keeping track of body weight, as well as access to educational information. The use of mobile health helped improve HbA1c levels in certain cross-section of patients with type 1 diabetes mellitus [11].

Fig. 1 A diabetes mHealth system

These data collected via manual user-input or via sensor nodes (e.g., smart blood glucose monitor) are sent to cloud-based health databases through cellular networks. From cloud computing services or medical centers, the data are collected for further analysis [12]. To foster key contextualization of these data, they are integrated with other clinical data sources like prescription registries, clinical registries, electronic health records, and laboratory-collected biomarkers [13].

Overview of hypertension mHealth system

Hypertension is when blood pressure is very high, blood pressure as the pressure applied by the flow of blood against the walls of the body's arteries [14]. Hypertension mHealth is also a subsidiary of hypertension telehealth setup. They differ only in some of the vital signs measured in the course of management of hypertension. The technologies available for management of hypertension are similar to those for diabetes. Smartphones and Bluetooth® enabled telemonitoring are new tools that are of increasing importance in hypertension management [15]. Figure 1 presents the typical components of an mHealth system for hypertension (both human and gadgets) and how they work together. As shown in Fig. 2, data like blood pressure, heart rate, rest, and sleep measurements are taken via sensor nodes or manually keyed into the hypertension mHealth app. Wearable devices such as watches can monitor BP with the use of electrocardiography (ECG) and photoplethysmography (PPG) signals. Data from these devices are sent to central servers for centralized access to all data through the internet. In the hypertension management system framework designed in [16], the data is then compressed and reduced to extract features and patterns. Extraction of the features is based on specified symptoms and directions. Some machine learning models can then applied to the extracted features to provide clues for diagnosis and treatment.

So, mobile health intervention has found footing in management of diabetes and hypertension, with lofty projected outcomes. Intriguingly, these projected benefits of mHealth to diabetes and hypertension, and a number of smartphone users have not necessarily translated to established advantages. Some literature have discussed these

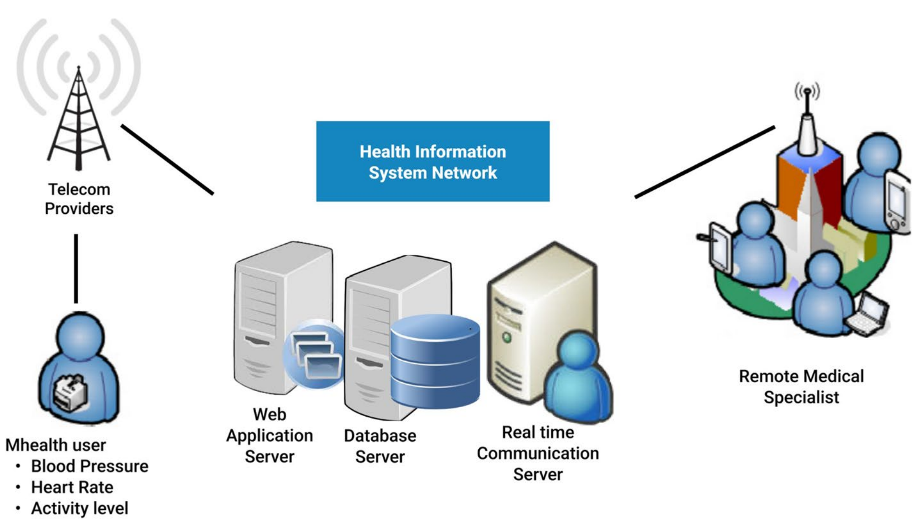

Fig. 2 A hypertension mHealth system

impediments to a great individual detail though in fragments, i.e., a few of them per literature. There has been shortage of literature that collate all the possible challenges in a single document. Feedback from users have been many of extensive kinds [17], which means having an exhaustive discussion on just a few of these challenges does not solve the varied nature of these concerns. A further outcome is the paucity of full-flavored mHealth systems equipped to handle the varied needs of users.

Though this work reviews the challenges from the perspectives of stakeholders (app developers, healthcare givers, and health system regulators and users), they are presented mainly as they affect the users/patients. We believe the ultimate is for users to attest to improvements post-intervention of any mHealth system adopted. With this work, extracting system requirements for development of diabetes and hypertension mobile health apps should be more efficient. The long-observed comorbidity of diabetes and hypertension inspired the combined review of mHealth systems for self-management of both chronic diseases in this work. As far back as 2010, a study in Hong Kong revealed that just 42% of diabetic patients had normal blood pressure and only 56% of hypertensive patients had normal glucose tolerance [18]. High blood pressure, or hypertension, often occurs alongside diabetes and obesity [19, 20]. So, to enrich our expose of challenges to mHealth use for management of diabetes and hypertension, we review mHealth apps for diabetes and hypertension. To understand what these apps should offer, first, we describe the various approaches to cost-effective management of diabetes and hypertension. Our concern in these approaches were mainly self-management approaches, which can be supported by mobile apps. For this reason, we focus on non-pharmacological and non-surgical approaches to management of diabetes and hypertension. This is what the "Approaches to management of hypertension and diabetes" section discusses. Next, in the "Machine learning in management of diabetes: review" and "Machine learning in management of hypertension: review" sections, we present AI (specifically, machine learning) interventions to management of diabetes and hypertension. In establishing this nexus between aforementioned mHealth, approaches to the management of the two co-morbid diseases and machine learning, we explore extant literature on machine learning as applied to the management of diabetes and hypertension to reveal the focus spread of machine learning (ML) research on the identified approaches to the management of diabetes and the extent of incorporation of machine learning into mHealth systems. In the "User expectation" section, we present user expectations from diabetes and hypertension mHealth systems, while in the "Review of Existing mHealth solutions" section, features of existing mHealth systems for diabetes and hypertension are reviewed. Finally, the "General challenges" section presents general challenges faced with diabetes and hypertension mHealth systems.

Approaches to management of hypertension and diabetes

While diabetes mellitus and hypertension cannot be cured, they can be managed both physically and psychologically. Non-pharmacological interventions aid in reducing the daily dosage needed for antihypertensive medication and interrupt or slow down prehypertension deteriorating to hypertension [21]. Raveendran et al. [22] list non-pharmacological methods to include bariatric surgery, medical nutrition interventions, and change of lifestyles. Besides nutrition, lifestyle changes include exercise, avoiding stress, and lowering alcohol consumption [21]. However, surgery as non-pharmacological approach is extrinsic to self-management of diabetes and hypertension and therefore not discussed in this work. Focus is on non-surgical non-pharmacological ways of managing diabetes and hypertension: dietary intervention, physical activity, sleep, and rest. The justification for inclusion of self-management approaches in this review of MobileHealth systems in management of diabetes and hypertension is that MobileHealth systems for such ailments are mostly geared towards self-care or self-management. It makes it pertinent to present an overview of such self-management approaches as later in this paper they help us understand and classify existing works on diabetes and hypertension management.

Dietary intervention

Dieting entails taking healthy diet while desisting from taking unwholesome foods and health-damaging substances [23]. Maladjusted eating attitude and eating disorders are serious conditions in type 1 diabetes mellitus, yet under-explored [9]. Because medication can have after effect or can be disastrous due its abuse and patient's internal body reaction to the medication, there is need to incorporate diet to the system [24]. Making a difference in a way of living such as eating wholesome meals, addition of adequate physical activities, and termination of smoking aids in obtaining an ideal blood pressure level [25]. Despite the fact that management of diet is greatly commendable as regards hypertensive patients, there is little knowledge with respect to the patients' diet control and how the set out rules are being followed [26].

Though high blood pressure and diabetes can be managed and controlled through a healthy diet, compliance to the diet prescription is an issue. Factors that illicit non-adherence are non-availability and cost of food prescribed, low level of education, age, flexibility of diet, and recommendation incomprehensible [27–29]. Low level of education can affect compliance by 70%, and older adult between the age bracket of 60 and 79 years are less likely to comply to recommendation [27]. Furthermore, based on interview conducted in [29], 39% of the respondents were unable to comply to diet prescription due to the rigidity of the diet. The same study also suggests that rather than persisting on stringent diet, the diet should focus on patients predilection. Diet management works best with physical activity (PA).

Physical activities

Diabetes and hypertension are under the aegis of metabolic syndrome (MetS) [19]. Obesity and physical inactivity are the popularly known cause for diabetes and hypertension [14, 30]. Engaging in physical activity daily lowers the possibilities of having diabetes and hypertension [31, 32]. All types of movement are termed physical activity, and these include sports, walking, cycling, and wheeling [33]. For diabetic patients, physical activity aims at improving cardiorespiratory fitness, enhanced vigor, improving glycemic control, reducing insulin resistance, enhancing lipid profile, reducing blood pressure (BP) level, and maintaining ideal body weight [34, 35]. In a case of hypertension, physical activity is encouraged due to its ability to reduce blood pressure by enhancing cardiorespiratory fitness (CRF) [36]. High level of physical activity can reduce blood pressure level by the rate of reductions ranging from 5 to 17 mm Hg for systolic BP and 2 to 10 mm Hg for diastolic BP. Physical activity is also proven to be very effective in avoiding incident hypertension for adult with prehypertensive and normal blood pressure level [37]. Apart from the benefits of physical activity in management of diabetes and hypertension, fitness apps were found in [38] to be most preferred mHealth app, with the attendant advantage of longest periods of long-term use by patients.

Sleep and restfulness

It is not only the activity that is impactful, rest and sleep (elements of inactivity) are too. Of all the lifestyle recommendations in [39]—sleep, restfulness, activity, heart rate, and diet—sleep-related recommendations were the highest in number. Restfulness was third highest. Many reviews have surmised sleep as a contributor to glycemic control, diabetes management, and diabetes-linked complications in type 1 diabetes mellitus (T1DM) patients [40]. However, sleep has not been significantly explored as an opportunity for management of diabetes [40] and hypertension. Blood pressure (BP) dips during sleep. This explains why sleep disorders, especially obstructive sleep apnea (OSA) [41] and insomnia [42], have positive relationship with hypertension because they interrupt BP dipping. The association of restfulness from sleep with cardiovascular disease (CVD) events was pronounced in subjects with younger age and female sex [43]. Evidence is sparse on which patient phenotypes of CVD patients can benefit the most in terms of BP reduction and positive impacts of insomnia and restless leg syndrome (RLS) therapy on BP [41].

Artificial intelligence in the management of diabetes and hypertension

The technology in artificial intelligence (AI) permits the analysis of real-time empirical data and constant training to improve comprehension [44]. In health sector, AI methods are used in studying patient's data and foretelling upcoming incidence and creating smart interface for communication with the patient improvement in his/her commitment with the treatment plan [45]. Diabetes and hypertension being chronic in nature and requiring frequent checks/tests has resulted in the production of high volume of medical data from wearable technology, for instance, that track data from patient physical activity via Bluetooth, as in Alazzam et al.'s design [46]. To collate, store, and learn data pattern [47] and predict patient health require artificial intelligence, say, machine learning [48]. This has brought on the development of blood pressure telemonitoring (BPT) for remote BP tracking. Blended with machine learning models, efficiency of BPT solutions is better tuned as viable tool to caregivers [49]. The non-pharmacological approaches in management of diabetes and hypertension discussed in the previous section have also benefited from AI. In [50], machine learning was used in increasing physical activity in diabetes mHealth system and in recommendations for sleep and restfulness in [39]. Our focus is on machine learning algorithms applied to management of diabetes and hypertension are reviewed in this section, with the specific management approach each algorithm has been used for. Deep learning was not considered because it generally requires high computational power and has the behavior of a black-box approach, which discourages application in a medical context [51].

Machine learning in management of diabetes: review

Machine learning is a trending area where computational algorithms are created to imitate human intelligence through learning [52]. Machine learning makes it easier in identifying chronic diseases, as opposed to the manual ways of diagnosing chronic disease which are frantic, time-consuming, and error-prone [53]. Furthermore, machine learning can be used to effectively prescribe diet for diabetic patients. It can also help in predicting if a person will be diabetic or hypertensive from the data provided. In [50], a text-message-based mobile app, "DIAMANTE," built by Audacious Software is studied. This application tracks step counts by pooling from Google Fit, Apple HealthKit, or the built-in pedometer on patients' phones. The app determines motivational messages to display to user based on step-count per day. The reinforced machine learning algorithm in the app assesses which motivational message and which time period of the day (in intervals of two and a half hours) is predicted to maximize the number of steps walked the next day. The app also assesses engagement measures; machine learning was used to measure times that the app was opened and time spent reading. Summarily, the areas of diabetes research that have had application of machine learning are prediction, diagnosis, etiopathophysiology, and therapy [54].

There have been survey works on ML applied to diabetes research. The work in [54] presents extensive survey of papers on ML and data mining methods in diabetes research. Of the various aspects of diabetes research, machine learning application to prediction and diagnosis has been the most prominent with support vector machines (SVM) being the most successful and most used ML algorithm [54]. However, information was not provided as to the distribution of the ML algorithms over the various areas of diabetes research. Also, performance of the algorithms was not presented. The review in [55] evaluated machine learning algorithms previously applied to the prediction of type 2 diabetes mellitus (T2DM) using three diabetes datasets in a unified setup and compared their performance in terms of accuracy, measure of a test's accuracy (*F*-measure), and execution time, with bagging-LR being the most accurate for a balanced dataset, and random forest (RF) is the most accurate for imbalanced dataset (bagging-LR meaning logistic regression (LR) improved by bagging, an ensemble learning technique that helps to improve the performance and accuracy of machine learning algorithms). Prediction is just one of the research areas for management of diabetes. Also, whether accuracy, *F*-measure, and execution time or any other combination of performance metrics are the most considered/impacting remains to be seen.

Therefore, in this review, the key research contributions in this review of machine learning application to diabetes management are to:

- Show where emphasis have been on, be it on prediction, diagnosis, etiopathophysiology, or therapy aspect of diabetes research
- Show how much of machine learning (ML-based) treatment of diabetes has interfaced with mHealth systems
- Show most considered and impacting ML algorithms and their performances

A total of 20 journal papers covering 2015 to 2022 were reviewed: 9 from SpringerLink, 9 from ScienceDirect, and 2 from other sources.

Review findings (ML in diabetes management)

1. Application of ML to diabetes self-management approaches: Four purposes of machine learning application to diabetes research were observed: therapy, prediction (P), and diagnosis (D), the extra purpose being measurement of blood glucose level (BGL). In the area of therapy, dietary therapy (TD), physical therapy (TP), and rest therapy (TR) were considered. As extracted from Table 1 and summarized in Fig. 3, prediction of diabetes had the most application of machine learning at 52%, while ML application to diagnosis of diabetes stood at 21%.

This confirms the observation made in [54] that diabetes prediction and diagnosis has had the most focus of ML algorithms, with it tilting more to diabetes prediction [56]. Half of the times diagnosis was considered, early diagnosis, P(Early), was of interest. Observe that some literatures in Table 1 considered more than one purpose, like [46] and [57]. For instance, in [57], LR, RF, and MLP were used for diagnosis, while LR, RF, and LSTM were used for prediction. Further in our review, therapy was considered for only 14% of the literature, specifically dietary (5%) and physical therapies (9%). Rest therapy was not applied in any of the reviewed literature. Blood glucose level (BGL) monitoring/measurement was the purpose of application of ML to diabetes research in 13% of the reviewed literature, nearly equally focus of ML on all forms of non-pharmacological and non-surgical therapies highlighted in this work. These findings are explained in greater detail as follows:

(a) Identification of patient physical activity: In [46], support vector machine (SVM) and decision tree machine learning models were used to identify two tasks: sitting and standing. Both models were 86% accurate for those tasks. The researchers were positive that it could become a standard mechanism for diabetes management depending on the results of a pilot study with real patients.

Investigation of status of falls and identification of key risk factors for fall in T2DM patients was done in [58] using logistic regression and random forest classifiers. Logistic regression showed that fasting C-peptide level, dorsiflexion, and knee extension strength were autonomous predictors of falls. The random forest classifier placed grip strength among the top 5 key variables for falls.

(b) Identification of predisposition to diabetes: Using logistic regression (LR) and gradient boost (GB), a predictive model with respectable sensitivity and selectivity was built in [59]. Using patient demographic data (of Canadians) and results from laboratory tests, the work identified patients at risk of having diabetes mellitus. The area under the receiver operating characteristic curve (AUC-ROC) was used to evaluate the discriminatory capability of these models. The AUC-ROC for the proposed logistic regression model was 84.0%, and it was 84.7% for the proposed GB model. For sensitivity, logistic regression performed at 73.4%, and it was 71.6% for the proposed GB model. Age, high-density lipoprotein, fasting blood glucose, triglycerides, and body mass index were the prime predictors in logistic regression model. In [60], logistic regression (LR) model demonstrated that 7 factors (education, age, BMI,

Table 1 Summary of machine learning algorithms for diabetes management in reviewed literature

Author/year	Purpose	ML algorithm	ACC	SEN	SP	PR	ROC-AUC	F	NPV	Dataset	DMS Inc.
[73]/2020	P(risk)	LR, RF, SVM, KNN, bagged, bagged CART	CART (94.3)	CART (99.9)	-	CART (94.2)	-	CART (96.9)	-	Bangladesh: DHS	No
[74]/2022	P(risk)	RF, XGB, DNN	XGB (87.2)	-	-	XGB (62)	DNN (85.7)	DNN (67.2)	-	TLGS	No
[71]/2021	P	LR, LDA, FDA, DT(C5)	LDA (67)	LR (75)	LDA (67.3)	LR (0.4)	-	-	99.9	CONSTANCES, SNDS	No
[75]/2019	P	LR, RF, SVM, XGB	-	XGB (95.4)	-	XGB (89)	XGB (89)	-	-	NHANES	No
[76]/2018	P	SVM, MLP, LR, NB, C4.5, RF, HPM	HPM (92.56)	HPM (93.4)	SVM (98.79)	HPM (91.5)	-	HPM (92.44)	-	Wu et al. [77]	No
[78]/2020	P	LR, RF, SVM, KNN, NB, GB	RF (88.76)	-	-	-	RF/GB (86.28)	-	-	HMIS, Kano	No
2020	P	LR, RF, SVM, KNN, NB, GB	RF (98.48)	RF (95.57)	-	RF (98)	RF (97.78)	RF (97.73)	-	PIDD	No
[64]/2015	P	RF, KNN, DT	DT (86.46)	DT (86.56)	KNN (89)	-	-	-	-	UCI	No
[65]/2019	P	LR,RF, SVM, KNN, DT (J48)	DT (94.4)	-	-	-	-	-	-	PIDD	No
[68]/2022	BGL	LR, RF, SVM, KNN, NB, XGB, DT	RF (84)	-	-	-	-	-	-	iGLU device, PIDD	Yes
[46]/2021	TD, TP, BGL	SVM, DT	SVM/DT (86)	-	-	-	-	-	-	UCI, PIDD	Yes
[57]/2021	D (Early) and BGL	LR, RF, MLP	MLP (86.08)	MLP (85.1)	-	MLP (86.6)	-	-	-	CGM Device	Yes
	P	LR, MA, LSTM	LSTM (87.26)	-	-	-	-	-	-	CGM Device	Yes
[69]/2022	P	LR, RF, SVM, KNN	RF (98.4)	RF (98.7)	RF (91.6)	RF (99.1)	RF (98.4)	RF (98.9)	-	IoT sensor, question-naire	Yes
	P	LR, RF, SVM, KNN	RF (75)	RF (78.9)	LR/SVM (66.6)	LR/SVM (85.6)	RF (97.8)	LR/RF/SVM (81.3)	-	PIDD	No
[59]/2019	P	LR, RF, GB	-	LR (73.4)	GB (83.7)	-	GB (84.7)	-	-	CPCSSN	No
[60]/2020	P	LR, RF, NB, DT, AB	LR+RF (94.25)	-	-	-	LR+RF (95)	-	-	NHANES	No
[61]/2016	D	DT (J48), AB, bagging	-	-	-	-	AB (≈81.67)	-	-	CPCSSN	No
[66]/2017	D	GPC, LDA, QDA, NB	GPC (81.97)	GPC (91.79)	GPC (63.33)	GPC (84.91)	-	-	GPC (62.5)	PIDD	No
[70]/2022	D	RF, NB, DT (J48)	RF (79.57)	DT (88.43)	RF (75)	RF (89.4)	RF (86.24)	RF (85.17)	-	PIDD	Yes
[62]/2021	D(Early)	RF, SVM, GB, AB	RF (99.35)	RF (99.01)	RF (100)	-	-	-	RF (98.15)	PIDD	No
[58]/2022	TP	LR, RF	RF (77)	RF (52)	RF (82)	-	RF (75)	-	-	Questionnaire	No

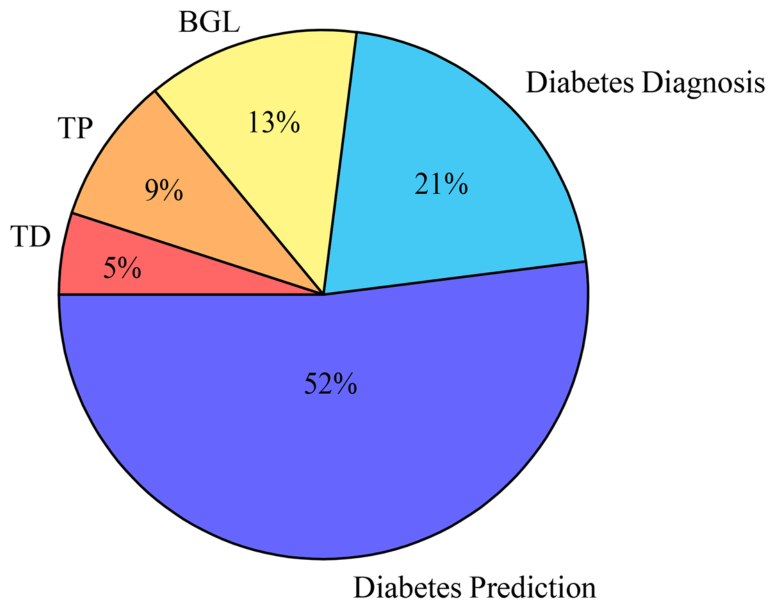

Fig. 3 Distribution of diabetes ML works according to self-management approaches

direct cholesterol, systolic BP, diastolic BP, and total cholesterol) out of 14 are diabetes risk factors. The overall accuracy of this ML-based system was 90.62%. The combination of LR-based feature selection and random forest (RF)-based classifier gave 94.25% accuracy for K10 partition protocol.

The study in [61] evaluated the performance of Adaptive Boost (AdaBoost) and bagging data mining ensemble techniques using J48 (c4.5) decision tree as a base learner along with standalone data mining technique J48 (c4.5). The work achieved accurate classification of patients with diabetes mellitus using diabetes risk factors with consideration for three adult groups in Canadian Primary Care Sentinel Surveillance Network (CPCSSN) database, viz., below middle-aged adults, middle-aged adults, and adults older than 55 years. The work identified AdaBoost ensemble method to outperform bagging and standalone J48 decision tree in accurate identification of diabetes patients.

(iii) Diagnosis of diabetes: The GB and logistic regression models in [59] may have performed better than the random forest and decision tree models for identification of people at risk of having diabetes, but for early diagnosis of diabetes, random forest (RF) model, with accuracy (ACC) of 99.35%, holds more significant promise than GB model (93.51%) and more so AdaBoost (88.31%) and SVM (85.06%) [62]. Also, sensitivity (SEN) and specificity (SP) were metrics in which RF (99.01% and 100%) outperformed GB (97.06% and 98.08%), AdaBoost (94.51% and 87.77%), and SVM (89.72% and 91.49%), respectively. In [63], diabetes and prediabetes were predicted using artificial neural networks (ANNs), logistic regression, and decision tree models. Participants were drawn from two localities in Guangzhou, China. Recruited were 735 diabetes or prediabetes patients and 752 normal controls. With the use of questionnaire, information on family diabetes history, demographic characteristics, lifestyle risk factors, and anthropometric measurements was obtained. In the order of accuracy, sensitivity, and specificity, the models performed thus as follows: LR 76.13%, 79.59%, and 72.74%; ANN 73.23%, 82.18%, and 64.49%; and the decision tree (C5.0) 77.87%, 80.68%, and 75.13%. The best classification accuracy and specificity were achieved by decision tree (C5.0).

Four models (SVM, KNN, DT, RF) were compared for prediction of diabetes mellitus in [64] using 8 important attributes of Indian patients: triceps skin fold thickness, number of times pregnant, plasma glucose concentration, diabetes pedigree function DBP, 2-hour serum insulin, body mass index (BMI), and age. In terms of accuracy, sensitivity, and specificity, random forest algorithm, with all 100% score, outperformed SVM, K-nearest neighbor (KNN), and decision tree (J48). In the order of accuracy, sensitivity, and specificity (in %), SVM had 77.73, 51.37, and 71.09, KNN ($k = 3$) had 85.68, 79.47, and 89, and decision tree (J48) had 86.46, 86.56, and 86.4. A similar work was done in [65], considering same attributes and similar classifiers (LR with SVM, KNN, and decision tree (J48)), except random forest. Similar results were got as decision tree (J48) had higher accuracy than the rest, with bootstrapping (78.43%) and without bootstrapping (94.4%). KNN ($k = 3$) had second highest accuracy without bootstrapping (72.2%), but with bootstrapping, KNN ($k = 1$) had second highest accuracy (93.79%). The Pima Indian Diabetes Database (PIDD) was used. With accuracy of 81.97%, sensitivity of 91.79%, and specificity of 63.33%, Gaussian process (GP)-based classification technique performed better than linear discriminant analysis (LDA), naive Bayes (NB), and quadratic discriminant analysis (QDA) [66].

(iv) Detection of inaccurate diabetes data: Decision tree machine learning algorithm was used in detection of sources of inaccurate data and delivery of quality information. The algorithm was able to classify the diabetes data as accurate or inaccurate [67].

While ML has had respectable use in physical health, chronic disease management, and remote patient monitoring, the same cannot be said about its use in chronic disease detection. In [56], a paltry 24% of the journals reviewed discussed ML models for diabetes detection. The 24% is also shared by cardiovascular and respiratory conditions. Machine learning has been applied to good results in guaranteeing data accuracy and information integrity in diabetes mHealth.

2. Incorporation of ML into diabetes MobileHealth systems: The last two columns on Table 1 are for dataset source and answer to whether or not the ML models were incorporated into a diabetes mHealth system (DMS). Only 25% of the reviewed works had any form of integration into an mHealth system either in form of mHealth app [46] or an IoT devices/sensors [57, 68–70]. The use of IoT devices/sensors were primarily for collecting BGL data.
3. Performances of ML algorithms in diabetes research: As shown in columns 4 to 10 of Table 1, the machine learning algorithms used in the reviewed works were logistic regression (LR), linear discriminant analysis (LDA), Fisher's discriminant analysis (FDA), quadratic discriminant analysis (QDA), decision tree (DT), gradient boost (GB), random forest (RF), long short-term memory (LSTM), support vector

machine (SVM), K-nearest neighbor (KNN), naïve Bayes (NB), artificial neural network (ANN), deep neural network (DNN), extreme gradient boost (XGB), AdaBoost (AB), multilayer perceptron (MLP), moving average (MA), bagging, regression tree (bagged CART), and Gaussian process-based classification (GPC). Performance metrics observed in the literature include accuracy (ACC), sensitivity (SEN), specificity (SP), precision (PR), area under curve (ROC-AUC), *F*-measure (F), and negative predictive value (NPV). There were others like miscalculation rate, kappa, MCC, false discovery rate (FDR), false negative rate (FNR), false positive rate (FPR), and detection rate. They were not captured in the table (Table 1) for want of space and the fact that none occurred more than twice in the reviewed literature.

The best performing ML algorithm under each performance metric is stated with the percentage level within braces, e.g., LDA predicted diabetes most accurately in [58] at 67%. Where the ML algorithm is not stated in the cell, it means all algorithms used shared that maximum value, e.g., in [71], all the ML algorithms used in the work had NPV score of 99.9%. The four (4) most considered performance metrics were accuracy (90%), ROC-AUC (55%), sensitivity (50%), and specificity (45%). This supports the use of accuracy and ROC-AUC metrics, for instance, in [72], in deciding best model for diabetes prediction. Out of the three performance metrics considered in [55], only accuracy was confirmed to be among most considered. Our review places random forest (RF) algorithm as best performing in accuracy (40% of the time), ROC-AUC (30%), sensitivity (20%), and specificity (10%). For context, this was not because of a superior frequency of deployment of RF, as number of times of use of random forest (13) was not necessarily the highest logistic regression had fourteen (14) occurrences. Contrary to SVM being most prominent ML algorithm in [54], random forest was the best performing algorithm across all metrics, for all purposes covered in the literature. Tree-based algorithms were also found in [72] to be best performing, specifically random forest algorithm. The observation of DNN's sub-par performance in [72] could neither be confirmed nor refuted in our review. There was not enough data on this as DNN happen to be used only once in all the literature we reviewed. Though in that one time, it outperformed RF and XGB in *F*-measure and AOC-AUC metrics.

4. Diabetes dataset: The dataset used in [71] was sourced from CONSTANCES linked with French Administrative Healthcare Database (SNDS). Other sources were National Health and Nutritional Examination Survey (NHANES), Tehran Lipid and Glucose Study (TLGS), Health Management Information System (HMIS) in Kano, Intelligent Glucose (iGLU), Pima Indians Diabetes Database (PIDD), UCI Machine Learning Database, Continuous Glucose Monitoring (CGM), Internet of Things (IoT) sensor, Canadian Primary Care Sentinel Surveillance Network (CPCSSN), and Bangladesh: Demographic and Health Survey (DHS).

Machine learning in management of hypertension: review

The key research contributions in our review of machine learning application to hypertension management are to:

- Show the aspects of research on hypertension prediction using machine learning; and the distribution of emphases.
- Show how much of machine learning (ML-based) treatment of hypertension has interfaced with mHealth systems
- Show most considered and impacting ML algorithms and their performances

There have been two approaches in application of machine learning techniques in researches on high blood pressure: hypertension detection and blood pressure monitoring. The former is classification problem based on clinical data, while the latter is handled as a regression task [79]. Martinez-Rios et al. [79] reviewed works applying machine learning algorithms for classification of hypertension patients and regression algorithms used for blood pressure estimation. Also of interest was integration of machine learning into mHealth systems for management of hypertension. To identify existing works on this, we did search of various combinations of the terms referring to "machine learning," "neural network," "deep learning," "detection," "diagnosis/prognosis," "mHealth," "hypertension," "high blood pressure" on PubMed and Google scholar. As eligibility criteria, only original researches written in English were included in this review. Excluded were studies involving pregnant women and patients just undergone surgical procedure. Articles on prediction of hypertension in persons below 18 were excluded. Study selection was done in two steps: in the first step, titles and abstracts were screened according to the eligibility criteria. Full-text of articles selected from step 1 were further checked for eligibility. A total of ten works were on the final shortlist.

From available studies, the two major areas of ML application to management of hypertension were identified to be detection and blood pressure estimation based on physiological variables. The former is mainly on classification models for hypertension detection, while the latter is mainly a regression problem. Literature reviewed covered both genres, estimating blood pressure values from other signals to drive use of noninvasive and continuous measurements [79]. Most common signals for generation of predictors are electrocardiography (ECG) and photoplethysmography (PPG). While home BP monitoring based on cuffs offers instantaneous readings, ambulatory blood pressure monitoring (ABPM), though more expensive, provides automatic BP reading over extended periods of time, at intervals [80].

Review of existing literature on machine learning in hypertension management

In [81], for the first time, a multi-verse optimization (MVO) algorithm is integrated with TQWT for selecting optimum tuning parameters to decompose the input BCG signals into more representative SBs. To detect hypertensive BCG signals, eleven statistical features are evaluated from each SB. Among them, a set of seven statistically significant features are selected by applying the Kruskal–Wallis test and fed to a K-nearest neighbor (K-NN) classifier with six different kernels using a 10-fold validation scheme. The highest classification accuracy of 92.21%, sensitivity of 92.96%, and specificity of 91.60% are achieved using a weighted K-NN classifier. The work in [81] presents a non-parameterized approach for the optimal decomposition of BCG data to detect HPT more accurately. The primary benefit of the proposed support system is that it can detect HPT patients with high accuracy by reducing the clinician's workload.

In [51], wavelet scattering transform (WST) as a feature extraction technique was used to obtain features from PPG data and combined with clinical data to detect early hypertension stages by applying early and late fusion. PPG features extracted from the wavelet scattering transform in combination with a support vector machine can classify normotension (NT) with SBP < 120 mm Hg and DBP < 80 mm Hg and prehypertension (PHT) with SBP ranging from 120 to 139 mm Hg and/or DBP 80 to 89 mm Hg, with an accuracy of 71.42% and an F1-score of 76%. Interestingly, classifying normotension and prehypertension using the features extracted from PPG signals via wavelet scattering transform and physiological variables such as BMI, age, and heart rate presented no improved performance in accuracy and F1-score. In [82], five ML algorithms were applied to echocardiographic pulmonary hypertension (PH) prediction, viz., random forest of classification trees (RFc), lasso penalized logistic regression, random forest of regression trees (RFr), boosted classification trees, and SVM. Cross-validation (CV) scheme used was using a 10 times 3-fold. AUC achieved by the machine learning algorithms include random forest of regression trees at 87%, support vector machines at 83%, lasso penalized logistic regression at 78%, boosted classification trees at 80%, and random forest of classification trees at 85%. Parameters used were echocardiographic (Echo) parameters. Model training and testing in [83] used a dataset of 29,700 samples acquired via physical examination. The objective was to identify easy-to-get risk factors of hypertension, using univariate logistic regression analysis. The work utilized 10-fold cross-validation to optimize four models: CatBoost, RF, MLP, and LR. RF model performed best across metrics considered, viz., accuracy of 0.82, AUC of 0.92, specificity of 0.81, and sensitivity of 0.83. The primary risk factors identified were family history, BMI, waist circumference, and age, while in [84], age, wealth index, BMI, marital status, and working status were the primary risk factors when least absolute shrinkage operator (LASSO) was used as risk identification method. Furthermore, age, marital status, BMI, diabetes, and region were the primary risk for hypertension when support vector machine recursive feature elimination (SVMRFE) was used. Each of LASSO and SVM-RFE was combined with ANN, DT, RF, and GB, with the combination SVMRFE-GB providing best accuracy at 66.98%, recall at 97.92%, F-measure at 78.99%, and AUC at 0.669 compared to others. The hypertension data in [84] was extracted from a demographic and health survey done in Bangladesh between 2017 and 2018, which included 6965 people between of ages of 35 and above. Alkaabi et al. [85] identified age, history of high cholesterol, history of diabetes, education, employment, physical activity, waist circumference, tobacco use, gender, employment, education level, physical activity, mother's history of high blood pressure, sex, and adequate intake of fruits and vegetables as principal predictors of hypertension, in descending order. The data was drawn from Qatar biobank, having 987 records of residents 18 years and above.

In [86], gradient boost, regression partition trees (Rpart), RF, and Ensemble were the machine learning models used in prediction pulmonary artery hypertension (PAH). It was specifically aimed at identification of the diagnostic biomarkers in order to achieve early diagnosis of patients at risk of PAH. Plasma from sixty-four native patients with pulmonary artery hypertension (PAH) and 43 healthy controls were profiled for microRNA. Two (miR636 and miR-187-5p) out of the 20 microRNAs considered were picked by all feature selection methods adopted in the work, as they could predict PAH with high performance: best accuracy was achieved with XGB (83%), precision of 83% with both RF and XGB, and ROC-AUC of 84% with RF.

In [87], ML was used for detection of hypertension using population-based surveys. Dataset used was secured by integrating data from health and demographic survey in India, Bangladesh, and Nepal. The variables in the dataset were hemoglobin, blood pressure, sociodemographic and economic factors, weight, height, and random blood glucose. Six commonly used ML-based classifiers used were as follows: linear discriminant analysis (LDA), decision tree (DT), gradient boosting machine (GBM), random forest (RF), extreme gradient boosting (XGBoost), and logistic regression (LR) to predict hypertension and its risk factors. There were 818,603 participants, out of which 82,748 (10.11%) had hypertension. Age and BMI were identified as prime risk factors for hypertension. In a lower order of significance were BP, taking medicine to reduce blood pressure, education, and doctor's understanding of high blood pressure. LDA, GBM, XGBoost, and LR demonstrated highest accuracy at 90%. Apart from decision tree (DT) which achieved precision value of 91%, other algorithms performed with 90% precision. LDA, GBM, XGBoost, and LR achieved highest recall value at 100%. In F1-score, LDA, GBM, XGBoost, and LR scored 95%. All the algorithms had log loss values below 6%.

Sakr et al. [88] used LogitBoost (LB), artificial neural network (ANN), Bayesian network classifier (BN), support vector machine (SVM), locally weighted naive Bayes (LWB), and random tree forest (RTF) in predicting the individuals at risk of developing hypertension, using data from cardiorespiratory fitness. Dataset used comprised of treadmill stress testing undergone by 23,095 patients. The data was collected between 1991 and 2009. The variables captured in the dataset include data on diagnosis, vital signs, and clinical laboratory tests. Random forest performed best across all metrics considered: sensitivity (69.96%), specificity (91.71%), precision (81.69%), ROC-AUC (93%), and F-measure (86.70%).

Review findings (ML in hypertension management)

1. Aspects of hypertension prediction using ML Table 2 presents a summary of the works reviewed on machine learning prediction of hypertension. There were three main categories of researches in this area: hypertension prediction (Hyp. Pred.) [76, 82, 83, 86, 88, 89], prediction of risk factors [84, 85, 87], and prediction of prehypertension (PHT) [51]. Hypertension prediction ranked highest in statistics Most recurring risk factors associated with hypertension were observed to be BMI and age. The three works that predicted hypertension risk factors [84, 85, 87] all recommended that biochemical markers be introduced so as to improve the ML algorithms and achieve real life evaluations.
2. Performances of ML algorithms in hypertension research: The machine learning algorithms used in the reviewed works as shown in columns 5 to 11 of Table 2 were logistic regression (LR), regression partition trees (Rpart), linear discriminant analysis (LDA), decision tree (DT), support vector machine (SVM), random forest (RF),

Table 2 Summary of machine learning algorithms for hypertension management in reviewed literature

Author/year	Purpose or class	ML algorithm	Data Desc.	ACC	SEN	SP	PR	ROC-AUC	F	NPV	Dataset	HMS Inc.
[82]/2019	Hyp. Pred. (PH)	RFr, RFc, LLR, Boosted C5.0, SVM	Echo	RFc (85)	SVM (95)	RFr/RFc (67)	RFc (90)	RFr (87)	SVM (76)	-	HMIS	No
[89]/2020	Hyp. Pred. (PH)	LB, LDA, SVM, KNN, DT, AB, GD, LR	13 Echo+RHC	LB (87)	LB (90)	-	LB (87)	LB (87)	LB (83)	LB (88)	-	No
[86]/2021	Hyp. Pred. (PAH)	XGB, Rpart, RF, Ensemble	-	XGB (83)	Rpart/XGB/ Ensemble (91)	RF/XGB (71)	RF/XGB (83)	RF (84)	-	XGB (83)	-	No
[83]/2021	Hyp. Pred. (based on easy-to-collect factors)	RF, CatBoost, MLP, LR	29,700 samples	RF (82)	RF (83)	RF (81)	-	RF (92)	-	-	UCI	No
[51]/2022	NT/PHT	SVM, LR, LDA, KNN, DT	PPG+WST	SVM (71.42)	SVM (52.38/90.47)	-	SVM (84.61/65.51)	-	SVM (64.70/76.60)	-	PPG-BP	No
	NT/PHT	SVM, LR, LDA, KNN, DT	C+S	SVM (64.29)	SVM (52.38/76.19)	-	SVM (68.75/61.54)	-	SVM (59.46/68.09)	-	PPG-BP	No
[76]/2018	Hyp. Pred.	SVM, MLP, LR, NB, C4.5, RF, HPM	175 samples	HPM (76.42)	HPM (70.27)	SVM/C4.5 (96.04)	HPM (78.79)	-	HPM (82.2)	-	Golino et al. [90]	No
[88]/2018	Hyp. Pred	LB, BN, LWNB, SVM, RF, ANN	23,095 samples	-	RF (69.96)	RF (91.71)	RF (81.69)	RF (93)	RF (86.70)	-		No
[84]/2021	Risk factors	ANN, DT, RF, GB, SVM, LASSO, SVM-RFE	6956 samples	SVMRFE-GB (66.98)	SVMRFE-GB (97.92)	-	-	-	SVMRFE-GB (78.99)	-	Survey	No
[85]/2020	Risk factors	DT, LR, RF	987 records	DT/RF (82.1)	DT/RF (82.1)	-	RF (81.4)	-	RF (81.6)	-	QBB	No
[87]/2022	Risk factors	RF, DT, XGB, GB, LR, LDA	818603 samples	XGB/GB/LR/ LDA (90)	=ACC	-	DT (91)	-	=ACC	-	Survey	No

random forest of classification trees (RFc), random forest of regression trees (RFr), lasso penalized logistic regression (LLR), CatBoost, K-nearest neighbor (KNN), artificial neural network (ANN), naïve Bayes (NB), deep neural network (DNN), gradient boost (GB), extreme gradient boost (XGB), AdaBoost (AB), multilayer perceptron (MLP), moving average (MA), bagging, regression tree (bagged CART), long short-term memory (LSTM), and LogitBoost (LB). Performance metrics observed in the literature include accuracy (ACC), sensitivity (SEN), specificity (SP), precision (PR), area under curve (ROC-AUC), F-measure (F), and negative predictive value (NPV). In accuracy, SVM proved most accurate in 30% of the works in which accuracy was measured, random forest in 22%, and XGB in 20%. As regards sensitivity, SVM had highest sensitivity score in 40% of the works in which sensitivity was evaluated, followed by RF with 20%. As regards specificity performance metric, RF was most effective in 80% of the works in which specificity was considered. Random forest algorithm also had the best scores in 80% of the works in which ROC-AUC was evaluated. In Table 2, where a couple of machine learning algorithms were separated by forward slash, it means all the listed algorithms shared same score in the metric under consideration, e.g., in [87], XGB, GB, LR, and LDA all had same accuracy score of 90%. Also, for [87], under sensitivity, "=ACC" means sensitivity had same score for same algorithms written under accuracy.

3. Incorporation of ML into diabetes MobileHealth systems: Regarding incorporation into an mHealth system, none of the works showed any link between the machine learning setup with an mHealth system.
4. Hypertension datasets: The dataset sources were health management information system (HMIS), blood pressure estimation from photoplethysmogram (PPG-BP), demographic and health survey (survey), and Qatar Biobank (QBB).

C+S stands for clinical and sociodemographic data, PH for echocardiographic pulmonary hypertension, PAH for pulmonary artery hypertension, RHC for right heart catheterization, Echo for echocardiography, and QBB for Qatar Biobank.

User expectation

Before critiquing available mHealth systems, it is important to peek into what diabetes and hypertension patients expect from a given mHealth solution at the point of adoption. Of all the stakeholders in the mHealth ecosystem, users are the most crucial. mHealth app for diabetes and hypertension should focus on helping the patients/end-users manage their health without stress. mHealth app for diabetes and hypertension is expected to have the following features: health information, dietary recommendation, tracking of blood sugar levels, tracking of blood pressure level, exercise recommendation, notifications and alerts, security of personal and health information, insulin and medication, weight and BMI, reducing risk trend chart view, logbook view, and finally integration with other devices [91–94]. Furthermore, diabetic app for self-management of diabetes should also focus on providing an avenue for the users to easily learn by providing help/support features, removing actions that are prone to errors, offering improved graphics and screen views, and motivating patients and integration of basic heuristic design concept [95]. Though usability is important, if users are at home with the utility of the app, they can overlook some usability deficiencies. Both digital and clinical distress should be considered when diabetes apps are part of the healthcare ecosystem [96].

In a study on hypertensive disorders of pregnancy (HDP), respondents recommended interoperability (i.e., integration of mHealth data in EHRs and such data made available to caregivers) [97]. On the matter of information communication, users asked for clarity especially in informing users on moment and frequency of blood pressure measurement, as well as modesty in communication of expected benefits to forestall disappointment when those results are not attained.

Review of existing mHealth solutions

In this section, a review of existing mHealth apps for management and control of diabetes and hypertension is made. The mHealth systems reviewed in this work

- All available free
- Were chosen based on ratings on google play and app stores and recommendations by renowned health information outlets like Healthline, MedicalNews, and Verywell Health. Healthline, for instance, has an exclusive team managing an ample medical web of over 150 medical professionals availing expert point of views, medical reviews, and clinical guidance. Healthline's medical professionals ensure that the information they release are correct, evidence-based, state-of-the-art, person-centric, and reliable [98].

To justify choice of cost-free apps for review, in [38], cost of mHealth apps was held by users as a critical driver of abandonment of mHealth apps. Furthermore, the risk of having hypertension, diabetes, and comorbidity were found to be remarkable in the unemployed demographic [99]. Comorbidity is considered the coexistence of both diabetes and hypertension. Some challenges with adoption and continued use of mHealth solutions for diabetes and hypertension are precipitated by low income of users or/and cost of the mHealth solution, e.g., prescription non-adherence [100, 101], and adoption and sustainability [102]. It is recommended in [102] that economic analyses of diabetes mHealth solutions should capture among others the cost of the mHealth solution to the patient. As recently as 2021, the World Health Organization (WHO) recommended the inclusion of sociodemographic dimensions of the hypertensive population (e.g., income) in order to achieve equity [103].

Functionalities of existing mHealth solutions for diabetes

In this subsection, functionalities of some mHealth solutions are explained. Explained first are ones for self-management of diabetes, viz.:

1. Bluestar Diabetes: BlueStar provides a number of useful functions to users like scheduled medicine reminders, tracking of blood glucose levels, and daily meal scheduling. BlueStar accommodates both type 1 or type 2 diabetic patients [104].

2. Glucose tracker and Diabetic diary: This app offers features like recording, labeling, and organization of tools to help the user create a thorough account of his/her journey.

It is meant for persons with type 1 or type 2 diabetes and also gestational diabetes. To keep record of the data that mostly concerns user, the user may add customized tags like “pre-bedtime” or “post-breakfast.” In addition, user can export his/her records to his/her healthcare provider [105].

3. Fooducate: Fooducate is used in management of diabetes with the use of diet and physical activity. This app has over 300,000 foods in its database. Users can simply classify the food according to its safety by scanning its barcode, which in return will display an A, B, C, or D. If a meal could not be classified in those four tiers, users are given recommendations on a more wholesome meal. It also makes it easy for users to keep record of and learn more details about the food they eat, such as added sugar and secret ingredients [106].
4. Glucose Buddy: The process of recording carbohydrate intake, medications, exercise, and blood glucose readings is made easier by Glucose Buddy’s user-friendly interface. Moreover, users can gain knowledge of how their lifestyle affects their diabetes management with the help of its custom awareness [107].
5. My FitnessPal: MyFitnessPal does calorie counting. It also allows users to keep tabs on their water, sugar, and carbohydrate intake, as well as their physical activity and meal time. Users can also write down their blood sugar readings and insulin shots in the app’s notes section [108].
6. Bezzy T2D: This app is mostly used for chats and communications, with secure forums where people can discuss topics like daily life, diet and nutrition, relationships, recently diagnosed conditions, mental health, and more. Feeling of being a part of community is useful, especially when it comes to health [109].
7. MySugr: MySugr provides estimations for the bolus dosage calculation, glucose monitoring, and carbohydrate counting. It also provides reports on the users’ blood glucose levels over the course of weeks, months, or even years. In addition, depending on the users monitoring, it will estimate their hemoglobin A1C. This app stands out due to its clear, personalized dashboard interface, flexibility, ability to connect with users’ glucose meter, and notifications that prompt user to provide further data in the future (like blood sugar levels after a physical exercise). It also helps the user collaborate with their doctor to modify their therapy and enhance the management of their diabetes using all the data and charts that are provided [110].
8. Diabetes:M: Diabetes:M on its part offers notifications for test time, a system for tracking and logging nutrition intake, incorporation with fitness applications, and a blood sugar trend mapping. Additionally, the app provides an insulin bolus calculation based on the added nutritional data. Trend graphs and charts over a range of periods can be viewed, putting glucose management back in user’s control [111].
9. Beat Diabetes: Beat Diabetes app is mostly for newly diagnosed patients with diabetes, as it offers lots of diabetes 101 knowledge from the foods to avoid to easy techniques to improve one’s physical activity and latest treatment choices and learn what issues to look out for [112].

10. One Drop for Diabetes health: The One Drop for Diabetes Health app is a diabetes management app that makes preferably activity options for the user based on their blood glucose data. With notifications and alerts, community sharing, and regular health statistics reports, the app also uses the users' diet, exercise, and medication information to assist them in creating a complete diabetes management plan. This way, users can monitor their progress and make necessary behavioral changes [113].

Summarized in Table 3 are the functionalities of diabetes mHealth solutions discussed.

Functionalities of existing mHealth solutions for hypertension

Having detailed features of some mHealth solutions for self-management of diabetes, next are the features of some mHealth solutions for self-management of hypertension (summary of these features are presented in Table 4):

1. Cardio: A heart fitness app "Cardio" makes use of pulse-reader technology to allow users to track their heart rate with just their fingers. The users' smartphone's camera light measures their pulse using the camera on the back of the device. Furthermore, it assists users to increase their numbers and aerobic capability with doctor's consent using the app's interval training circuit [114].
2. Blood Pressure Companion: This app is used to monitor vital signs, such as blood pressure and heart rate, and also alert the user in case of any problems that may require action. It also makes it easy to download precise data which can be made available to healthcare physician. Additionally, it can be used to track blood pressure, heart rate, and weight along a histogram that displays the pattern of measurements over time [115].
3. Blood Pressure Monitor: With the help of this app, users monitor their vital signs and manually enter them along with other information, such as prescription intake, to produce an unlimited lifetime representation of their patterns. Furthermore, the charts provided by the app can be used to learn how various components of users' health and treatment plan interact with one another [116].
4. Pacer: Pacer is designed to provide physical activity intervention to management of diabetes and hypertension. It records the number of steps taken by measuring the distance covered; it imitates having a walking partner and fitness coach in one device. The fitness aim focuses on the supervised exercises and customized fitness programs [117].
5. My Diet Coach: The software assists users in learning what motivates them, how to maintain focus and resist food cravings, and how to make tiny, healthy lifestyle adjustments. With My Diet Coach, user may set a weight reduction target and monitor his progress. User can observe his/her weight loss graphically thanks to the app's picture-based weight tracker. My Diet Coach offers inspiring advice and phrases, e.g., when a user succeeds, it rewards [118].
6. Quardio: This app gives a precise data on heart rate, blood pressure, and other indicators of cardiovascular health. A more comprehensive picture of heart's health is achieved from numbers when users mix visual input with other health measures like their weight, body fat, and muscle composition [119].

Table 3 Summary of diabetes mHealth systems and their features/limitations

S/N	App name/vendor	Diet Rec.	PA	BGL	Notify	Dig. Asst.	Prof. Sup.	Rep.	Rating	Platform
1	Bluestar Diabetes/ Well Doc Inc.	X	X	✓	X	X	✓	✓	4.3	iOS/Android
2	Glucose tracker/ Mel studio	X	X	✓	✓	X	✓	✓	4.8	iOS/Android
3	Fooducate/ Maple media	✓	✓	X	X	X	X	X	4.4	iOS/Android
4	Glucose buddy/ Azumo Inc.	✓	✓	✓	X	X	X	✓	4.0	iOS/Android
5	My fitness pal/ My fitness pal Inc.	✓	✓	✓	✓	X	✓	X	4.6	iOS/Android
6	Bezzy T2D/ Healthline	X	X	X	X	X	✓	X	4.5	iOS/Android
7	Mysugr/Mysugr GMbH	X	X	✓	✓	X	X	✓	4.5	iOS/Android
8	Diabetes:M/ Sirma Medical	X	X	✓	✓	X	X	✓	4.3	iOS/Android
9	Beat diabetes/ Tips book	✓	✓	X	X	X	X	✓	4.8	Android
10	One Drop for diabetes/One Drop	✓	✓	✓	✓	X	✓	✓	4.1	Android

7. HealthWatch 360: HealthWatch 360 is an app created to achieve nutritional objectives, by the use of scientific principles. The user chooses a health and wellness objective to start, like lowering blood pressure. The users will then receive daily data on their nutritional status from the app's algorithm along with a personalized nutritional plan [120].
8. Instant Heart Rate: Instant Heart Rate app converts the camera on the users' phone into a heart-rate monitor, and then shows the reading in less than 10 s. The users take the easy test while seated and gets the record of their heart rate and a graph of their pulse waveform, or they use the app's "StandUp" exam to gauge their level of fitness and weariness. The app logs users' beats per minute and includes a note section so they can keep track of what they were doing when the test was taken [121].
9. Pulse Point response: This app connects users with cardiopulmonary resuscitation (CPR)-trained communities that are prepared to help in a cardiac (or other) emergency before the arrival of emergency vehicles. This app utilizes the users GPS to alert nearby residents who have the ability to act fast and save lives before emergency medical services come. The app provides instructions to the closest automated external defibrillator while directing emergency personnel [122].
10. Hello Heart: The HIPAA (Health Insurance Portability Accountability Act)-compliant app Hello Heart delivers users daily data about their blood pressure and BMI as well as reminders to take their medications. To get started, users inquire about obtaining a code from employer or physician. Then, after signing up and entering their blood pressure data daily, they may observe variations on a weekly timeline and base their health decisions on those parameters [123].

General challenges

As advantageous as mHealth systems have proven to be in management and treatment of diabetes and hypertension, there has been some setbacks. These challenges can also be viewed as determinants to factor into design and development of diabetes and hypertension mHealth solutions. Challenges to developing and using mHealth solutions are manifold and could be introduced from the stakeholders' perspectives [124]. Istepanian and Al-Anzi [125] admit that balance between emerging considerations or perspectives will depend on how the various stakeholders from patients, healthcare providers, clinicians, medical and mobile health market businesses, and regulators will perceive such developments. Choukou [124] merges the stakeholders into four: user (patient), care provider, developer (design/technology), and management. Considering all stakeholders provides the advantage of not leaving out any setbacks plaguing mHealth systems for the two chronic diseases considered in this work.

Therefore, holistically, the challenges can be classified under design of the mHealth app, information/content, usability, functionality, ethical issues, security and privacy, and user-perceived value [126]. A couple more limitations are presented in [127] to include poor proof of its clinical value, poor connection with the healthcare system, and lack of acceptable assessment and documentation. Carrol et al. [127] affirmed security and privacy breaches as concerns in these mHealth solutions. For emphasis, in [128], set out rules for assessing mobile self-management apps for patients with long-term illness

Table 4 Summary of hypertension mHealth systems and their features/limitations

S/N	App name/vendor	Diet Rec.	PA	BP Tracking	Notify	Dig. Asst.	Prof. Sup.	Rep.	Rating	Platform
1	Cardio/Cardiio Inc.	X	✓	✓	X	X	X	X	4.7	iOS
2	Blood pressure companion/ Maxwell software	X	X	✓	✓	X	✓	✓	4.3	iOS
3	Blood pressure monitor/ Taconic System	X	X	✓	✓	X	✓	✓	4.6	iOS
4	Pacer/Pacer health	X	✓	X	X	X	X	✓	4.8	iOS/Android
5	My Diet coach/ Bending spoons S.P.A	✓	X	X	X	X	X	✓	4.5	iOS
6	Qardio/Qardio inc.	X	X	✓	X	X	X	✓	4.8	iOS
7	Health watch 360/ Gen Ben life science corp	✓	X	X	X	X	X	✓	3.7	iOS/Android
8	Instant Heart Rate/ Azumio Inc.	X	X	✓	X	X	X	✓	4.2	iOS/Android
9	Pulse Point Respond/ Pulse point salvation	X	X	X	X	X	✓	X	4.6	iOS/Android
10	Hello Heart/Hello heart	X	X	✓	✓	X	X	✓	4.7	Android

are grouped into four criteria which include engagement, functionality, usability, and information management. Our review of relevant literature yielded a total of 13 general challenges with diabetes and hypertension mHealth systems, viz.

Security and privacy

The most dreadful and technological roadblock in mHealth is the security and privacy of the health data [129]. Patients fear for health information compromise, considering that the rate at which health records are compromised is alarming. As cyber threats keep evolving, healthcare is the biggest prey [130]. Sadly, healthcare data violations were graded as highest priced in cost of a data breach report in the year 2020 with the average total cost of 3.86 million dollars per annum [131]. That figure rose to 4.24 million dollars in 2021 [132]. These present an ever-expanding weight of security and privacy concerns in self-management mHealth systems.

Functionality

Functionality in mHealth in this context can be seen as the features of mHealth apps that will enhance the users' engagement and overall app productivity. According to [133], functionality features include technical support, chat that connects all user of the app, notifications, and viewing of patients test result. Non-integration of technical support features greatly affects the app usability, and it also leads to loss of users as seen in [134].

The study conducted in [135] proved that functionalities such as medical monitoring, notifications, logs of blood glucose, blood pressure monitoring, diet, and physical activities which were implemented in [136–138] study have the ability to help users manage their diabetes, blood pressure level, and body weight. These routines varying from user to user make providing users with option of personalizing content another sought-after functionality [139]. Furthermore, Benjamin et al. [133] presented an observation from the patients using the mHealth app by [140]. It was seen that the users showed a great sign of containment, with the app rating of 90%; this is as a result of engagement with the users all-through the development process and also implementation of chat that connects the users which was very vital.

Usability

Usability is referred to the length by which a product can be used by a designated users to reach a particular aim with success, productivity, and containment in a defined frame of reference [141]. Further to this definition, we can state that a patient being able to use the mHealth app and navigate through it without difficulties will solve the adherence issue to some extent and also enhance patients' engagement to the app. Patients achieving satisfaction of their cardinal needs by using mHealth apps makes them emotionally bonded with the mHealth apps, with resultant overall improvement of well-being [142].

The issue of usability can be solved through provision of technical support and training of users. In the study conducted by Benjamin et al. [133], six of study participants gets assistance in using the app, by providing technical support for response to questions, assisting in downloads, or educating the users by phone; it was observed that a study without a technical support or assistance have a possibility of losing more customers, and this is as a result of the fact that there is possibility that the people that partook in the study do not have a technical knowledge to use the app. In the [141] study, a questionnaire-based approach was used to measure usability.

Additionally, substantial testing of mHealth app by end-users is of essence to disclose the pre-eminent technique and layout of the app for specific groups, which in other words will increase the usability of the mHealth app [143].

As an extension of what usability entails, users should be able to easily take their biomedical measurements with any peripheral device [144]. Also significant about usability are decision support functionalities and real-time feedback [145].

Information and content

The content and information provided in mHealth apps, how the information is portrayed, and the validity of presented information have a lot to do with the patients' recovery process [139]. Given that most patients surveyed in [146] held positive attitudes towards mHealth and had tertiary education, the authors recommended improvement of user awareness. It is expected that such level of education and keenness to learn about mHealth have already laid the groundwork for an awareness campaign. Presenting appropriate information on the app and the app's content will make the patients to have a good knowledge of the ailment. Also, the app should pay more attention on enhancing the connection between the patients and the ailment, rather than just curing the patients [133]. With amelioration of knowledge on ailment, partakers saw their ailment in a bad direction and their symptoms as more severe [147].

Interoperability

In medicine, interoperability entails that data is transferred accurately, successfully, securely, and consistently regardless of software applications, information technology systems, and networks in various platforms [148]. Scoping review of mHealth apps for self-management of cardiovascular disease in [149] revealed lack of interoperability of mHealth applications with other systems as a major challenge. So, while mHealth presents innovative approaches to enhance primary healthcare delivery in developing countries, its impact can be extended by improving interoperability with electronic medical records (EMR), patient health records, and electronic health records (EHR) [150, 151]. Though interoperability frameworks have been in existence, their accessibility and utility for connection of mHealth solutions to electronic records are relatively unknown in the developing world [150]. The power of an EHR lies not only in the data it contains, but how it is shared—health information becomes instantly accessible to authorized providers across practices and health organizations, helping to coordinate care efficiently [152], e.g., connecting patients' blood pressure reports to their electronic medical record for review by their physicians is one of the four major ways mHealth systems help patients manage hypertension [153]. Fragmentation of these technologies remains a considerable concern [154]. Interoperability uses standards [148], protocols, and interfaces to connect systems using fitting techniques and frameworks. Other connected issues factored in are jurisprudence, agreements, workflows, and privacy issues [154].

Interoperability is frequently described in terms of five "levels": technical, syntactic, semantic, organizational, and legal [155, 156]. From the literature review, four themes were identified: infrastructure, interoperability standards, data security, and usability. For clarity, the themes and levels were mapped to one another in the following manner. “Infrastructure” and “security” mapped to all five levels of interoperability, “standards” mapped to all except technical interoperability, and “usability” mapped to only organizational interoperability [150]. As would be seen later, the problem of lack of interoperability births other problems like data incompleteness and non-sustainability of mHealth solutions.

As a way forward, further findings in [154] present political and leadership support as key to realization of interoperability of mHealth applications and eRecord systems. One direction for this is the more robust regulation of eRecord systems. Supporting this is the findings in [157] that the absence of national agency and policy on mHealth and use of two systems in parallel are important deterrents of mHealth solution adoption in low- and middle-income nations. For example, there is the Agency for Integration, Diffusion, and Archiving of medical information (AIDA) in Portugal [158]. It is an agent-diversified and service-based platform that makes for interoperability between healthcare information systems. From a technical point of view for instance, a cloud middleware based on the Health Level Seven International (HL7) standard was demonstrated as capable of encoding and storing, as well as interoperating and integrating EHR data between different applications in different health facilities [159, 160].

Data incompleteness

When mHealth systems do not interoperate, there is bound to be data incompleteness, thus making interoperability between different electronic health records a partial solution to data incompleteness [161]. What consists data incompleteness is where we have incomplete information in relational databases; when a fact needs to be provided in a relation, meanwhile values for some needed columns are missing [162, 163]. Furthermore, based on interviews in [161], potential partners who can benefit and address the debacle of data incompleteness in electronic health records include the following: vendors of the EHR systems, organizations that provide data solutions, owners/managers of outpatient health facilities located in the rural regions, and health care process improvement organizations. If there are regulations compelling partnership of these players, data uncertainty and incompleteness would be ameliorated.

Unsustainability

Sustainability in the context of mHealth systems is the capacity for enduring satisfaction of user needs—whether those needs remain constant or extend [164]. The ability to handle growing needs and expanding resources is scalability component of sustainability. It is in the large part a challenge from the mHealth system developer’s perspective. Sustainability also dictates that an mHealth solution should be economically workable, environmentally tolerable, and socially fair [124, 165]. Pankomera et al. [166] give a case in point of mHealth applications, especially in developing countries, that are pilot projects and not centrally managed, say, by the government—a major player in regulation. They are mostly initiated by individual non-governmental organizations that target specific health care interventions. This lack of coordination foreshadows unsustainability in that knowledge gained from one project are not applied to subsequent projects. Also, these projects are not expanded once completed. This often means that the mHealth projects are discontinued. The lack of sustainability of mHealth projects wastes a lot of resources [166].

Aamir et al. [157] recommend understanding the matter of incremental innovation as a way of ensuring that resources spent on pilot mHealth interventions are enhanced, even to complete realization of their potential. As further way forward, Choukou [124] presents a step-by-step path for achieving sustainability from mHealth idea to sustainable mHealth solution. First is design, prototyping, and testing. Second is pilot testing involving evaluation of e-prototype, determination of both feasibility indicators, and measurable outcomes. Third is strategy at facility, national, and regional levels. This is where government, non-governmental organizations (NGOs), and academia at these three levels are collaborated with for more requirements/features of a proposed mHealth solution. Finally, the mHealth characteristics are set such as are efficient, evidence-based, economically viable, socially equitable, environmentally bearable, and sustainable. These characteristics also agree with ones advocated for in [165].

Prescription non-adherence

Prescription adherence or conformity often leaves much to be desired in adults with chronic diseases [167]. Adherence is defined as the degree to which the patient's behavior is in agreement with his or her physician's recommendations in terms regimen, quality, and quantity [168]. To mark how consequential non-adherence has been, in [39], non-adherence percentage was most significant for the top two most recommended lifestyle factors for hypertension management—sleep and restfulness.

Long-term prescription adherence is partly but significantly precipitated by culture [169]. One of such culture is associating credibility with years of experience. Some elderly patients have reported disobliging prescriptions from perceived inexperienced caregiver; adults between 60 and 79 years were found in [27] to be less likely to observe recommendations. The lack of face-to-face interaction in mHealth solutions means this cross-section of users is left without their usual credibility indicator. Another associate of prescription non-conformity is low income [100]. Fernandez-Lazaro et al. [170] recorded prescription non-adherence in 52% of the participants in their study. Participants numbering a total of 150 were interviewed over a course of 6 months from treatment inception. Even though these statistics have more to do with medication prescriptions, the way users treat prescription of non-pharmacological therapies is no different.

Modifications in treatment, shortage of information about medications, intangible number of follow-up visits, and lack of prescription reminders on mHealth apps are very likely to encourage disregard for prescriptions [170]. A study analyzing psychological techniques found some of those techniques potent in fostering prescription adherence by the elderly with chronic diseases. A combination of interactive communication with healthcare professionals, customized feedback messages, and varied functions was found to be most effectual [171]. Furthermore, appropriate levels of adherence can be optimally achieved via customized multifarious interventions which will consider factors with patients' enlightenment and their information needs [101]. Regarding user information needs, patient-directed feedback about BP trends is argued to be the most virulent tool in management of hypertension using mHealth systems [153]. Prescription adherence is in some cases very related to user engagement. A user engagement tool like SMS reminder improves adherence [172, 173]. Adherence dictates if the user records improvements from the mHealth intervention. Such improvements in turn foster belief and preserve user interest—a crucial ingredient of user engagement.

User engagement

User engagement has to with the standard of the user experience that focuses on desirable aspects of interaction and captivation by technology [174]. Fostering of long-term use of mHealth systems is the other ingredient of user engagement emphasized in [175]. Process appraisal of intervention trials pinpointed shortage of initial and enduring engagement of users as an affective curtailment of the benefit of mHealth interventions [176]. The WHO in [103] recommends long-term tracking of patients for better results in hypertension management. The lack of long-term user fidelity to the apps gives a reason for the report in [177, 178] that long-term effects of mHealth interventions are yet fairly convincing. Furthermore, even when user choice is instigated by cogent recommendations, the presentation of an mHealth app, in terms of functionality, is key to sustained use [179]. Diabetes, one of the ailments under review in this work, demands that patients maintain optimal blood glucose (BG) through regular tests. Devotion to this routine for a chronic disease is not easy [175], hence the need for motivation. That these are potential pieces that make up patient engagement is undisputed, but at its pivot, patient engagement is a matter of care-providers and patients' ethos [180].

The lack of engagement in the course of treating a patient is a perennial concern for health professionals, particularly those utilizing technology as a motivational factor [181]. The bedrock of user engagement is motivation. What the different approaches to user engagement have in common is motivation. Some of the motivational factors in use include goal management, navigation, interface design, notifications, depth of knowledge, data collection methods and tools, system rules, applicative recommendations, and user system fit [182]. Considered next are the key motivational factors for prolonged use of diabetes and hypertension mHealth systems, viz.:

1. Gamification: Health behavior change support systems (HBCSSs) is a promising research discipline which focuses on the use systems and services to influence health or wellbeing behavior [183–185]. Gamification is a fun approach to improving health behavior change, especially improving intrinsic interest in mHealth applications while reducing prescription non-adherence. The study in [181] proved gamification as a viable approach to promoting user engagement for a hypertension monitoring app. Evaluated in the study were 14 patients with hypertension, split into groups to establish if the addition of game components would inspire improved engagement in health care. The results showed gamification inspired engagement. Even better results were recorded in groups that had assistance of health professionals in that they spent longer time with the app and were inspired to maintain control of their health. Furthermore, the study in [186] explored the impact of gamification on users' tendency to sustained use of mHealth apps. Perceived usefulness, confirmation, and satisfaction were confirmed to have stimulating effect on continuance intention. In addition, the path and workings of users' feelings as regards self-reliance, relatedness,

and competence induced by interactions with different gamification components inspire persistence in the use of mHealth apps. Findings by Tran et al. [187] indicate that for medication adherence in mHealth apps, gamification, more than financial incentives, has been more widely studied. Across the retrieved articles, gamification alone (82%) recorded more use than financial incentives (9%) alone or a mix of the two (9%). Also, in [187], point-based features were the most dominant. Literature on the individual contributions of the gaming features is lacking. Gamification may prove advantageous, but the extrinsic interests it generates are the shortcomings [188]. Some of the adverse motivational results are user health behavior becoming over-dependent on gamified HBCSSs [189], distraction from health purpose [190], discouragement due to poor scores in the gaming [191], and trivialization of health context [192]. These can distract from promotion of adherence culture in users.

2. User expectation: User expectation though discussed is re-presented here as a motivational factor for user engagement. Privacy, one of the expectations users have, is a motivational factor. So much so that users in [175] recommended that mHealth systems that collect and share personal data should have succinct opt-in and opt-out feature to inspire usage. Other expectations are that the system should be provide high quality data, integrated view, timely self-management information, and feedback [175]. Adaptation of these details a user's customized features, which if not met discourages use of an mHealth system. User expectation is a sure way of achieving engagement. If user-centered features are to be improved on, stakeholders (especially users) must be involved extensively in development of mHealth systems [193]. Meanwhile, researchers mostly do not have sufficient experience in engaging patients as collaborators as they would research subjects [194]. The panacea to this is that mHealth developers and researchers should refine their elicitation of system requirements from users. Users involved on the other hand could be trained to offer telling and actionable input to the system requirements.
3. Participatory health technology: Social media is an example of participatory health technology [195]. While social interactivity feature of mHealth systems does not necessarily influence its adoption/choice decision [196], it motivates user engagement (continuance of use once chosen). People with disease history were more inclined to learning from data, as well as from others through social media fusion [175]. However, the state of social media and regulation landscape have brought on perceived susceptibility among other issues [197]. Therefore, attaining a balanced nexus between privacy and patient quest for health knowledge on the platform of participatory health demands patient empowerment, linking participatory health enabling technologies with clinical records, open data sharing agreement, and electronic consent [195].
4. Goal management: User engagement from goal management point of view may involve notification functionality on the mHealth app, sending text messages out to remind patients about to take their medication or schedule appointments for their next lab test. Also, patients can be considered engaged if they use mobile devices to observe vital signs like blood glucose level, blood pressure, or body weight. Vaghefi and Tulu [182] recommend synergy of user experience and goal management approaches to achieve sustained use of mHealth solutions for chronic diseases. Self-

monitoring requires functionalities where users can evaluate their own performance, which can ease attainment of their health objectives. Data tracking, checklists, and fact-finding tools were pin-pointed in [198] as three functionalities that favor goal-setting and achievement in an mHealth system. Regarding setting up of goals, many users favored having options in goal attainment evaluation tools.

Alternative approach for health behavior change (HBC)

Grady et al. [199] argue that though influencing positive health behavior by exploiting individual users and personal determinants of health has its place in public health, alternative method should be explored. They noted that the instigators of chronic diseases like diabetes and hypertension are multi-factorial and complex and thrive within institutional and societal environments and systems. Therefore, mHealth systems should as an alternative approach aim at modifying institutional systems to foster environments that nurture health behaviors. There is currently a shortage of mHealth systems adopting this approach.

Another relatively unexplored method to achieving HBC is self-compassion. Self-compassion has proven a key quality to encourage for promoting positive health behaviors [200, 201], due in part to its connection with malleable emotions. The desirable components of self-compassion are strongly positively correlated with health-promoting behaviors [202]. While self-compassion is kindness to oneself, health-promoting behavior is engagement in practices that promote well-being and health [203].

Weak recommendation system

The prevalence of diabetes and hypertension has resulted in an avalanche of mHealth apps to choose from to manage both chronic diseases. Inundated with options, users rely on recommendations of family and friends, perceived relevance, brand recognition, and user ratings, rather than evidence of effectiveness [199]. Others choose mHealth apps based on sheer number of downloads indicated, not number of current users, which in this case would be a better decision metric. Users require platforms that offer tested and evidence-based recommendation to sort out their confusion. Curated health app portals are one way. National Health Service (NHS), UK, has solved the problem. Curated health app portals (e.g., National Health Service Apps Library and the Public Health England One You App portal) appeared to engender user trustworthiness and alleviate data protection concerns [179]. This is because curated health portals publish or recommend mHealth apps that have proven results of effectiveness.

Compliance

If an mHealth application operates in a manner that consistently conforms with a rule, then it is said to be in compliance with the regulation [204]. Mobile health systems are less likely to have bugs, security issues, and poor design if it complies with software standards [205]. Moreover, for the purpose of licensing and certification, governmental and regulatory authorities demand conformity with applicable standards and rules [206], and establishments also need conformity with clearly defined rules from their suppliers to have a quality and clear production [207].

The problem and demands of many stakeholder groups are formulated as requirements that direct the building of software products [208]. Since the greater number of these demands are often derived from corporate stakeholders, such as customers or users, community stakeholders are becoming more and more important [209]. Governments and other organizations known as community stakeholders, establish laws, rules, and best practices which are considered as compliance requirements [210]. To help decrease mistakes, security issues, and bad design, mHealth applications like those for diabetes and hypertension should adhere to the health and software standards.

Fan et al. [211] present findings on major mHealth compliance violations, especially violations of General Data Protection Regulation (GDPR), a regulation to optimize privacy protection as incompleteness of privacy policy, the insecurity of data transmission, and the inconsistency of data collections. As medical equipment/devices are treated under strict regulations, so should mHealth solutions, since they are also qualified as medical devices [212].

Design and design framework

The proliferation of mHealth has not been accompanied by a corresponding growth in design guidelines for mHealth applications [213]. Design framework used in the development of mHealth systems can help resolve many of the contextual challenges with mHealth solutions afore-listed. For example, better understanding of user-preferred design features and functions of technologies is a way to achieve user engagement [214]. Another example is that designing diabetes and hypertension self-management apps without health behavior theory may lead to intangible promotion of prescription adherence [167]. Furthermore, Wei et al. [215] linked proper design of mHealth systems to good user experience and user engagement. All these prove design as the one-size-fits-all solution to most user-centered issues with diabetes and hypertension mHealth apps. Consequently, Farao et al. [213] encourage a synergy of the Information Systems Research framework and design thinking, for mHealth design in a developing, under-resourced scenario. What is more, Bhatia et al. [216] recommends addition of regulatory sandboxes as controlled and monitored real-world test setting for mHealth solutions prior to large scale deployment. This was as they observed that end-user demands and clinical shortcomings are often poorly recognized when designing solutions, contributing to a massive drop in usage, known as the “law of attrition” in electronic health.

Conclusions

Diabetes and hypertension are chronic illnesses that require management and control, and utilizing mobile technology to help patients manage their health is essential. Exponential increase in number of people with access to smartphones has made developing mobile health applications for management of diabetes and hypertension a viable and appealing approach to augmenting face-to-face caregiver-patient interactions. This work cataloged the general challenges impeding the expected advantages of mHealth intervention. They include issues with security and privacy, functionality, interoperability, usability, data incompleteness, unsustainability, user engagement, compliance, prescription non-adherence, and weak recommendation system. Though the challenges were mostly user-centered challenges, there are also ones from perspective of other stakeholders like mHealth developers and health policy makers. All these challenges could be addressed by how the design framework of an mHealth system is laid out. Since the use of diabetes and hypertension mHealth solutions is mostly about self-management, the work identified self-management of the two non-communicable diseases to be mostly of non-surgical and non-pharmacological genre. Dietary management, physical exercise, and sleep were identified to be cost-adaptive and cost-effective alternatives that fit the two classes.

The use of mHealth solutions has not evolved past advancements in treatment (diagnosis and early detection) of these two co-morbid diseases anymore than the treatment has evolved past headway in machine learning in healthcare. This necessitated the review on machine learning as applied to diabetes and hypertension, with the objective of understanding the aspects of diabetes and hypertension research approached by machine learning and which machine learning models have impacted more in terms of performance and extent to which there has been a nexus between machine learning and mHealth still with bias on diabetes and hypertension.

Abbreviations

AB	AdaBoost
ANN	Artificial neural networks
API	Application programming interface
AID	Automated insulin delivery
AIDS	Agency for Integration, Diffusion, and Archiving of medical information
AUC	Area under the ROC curve
BGL	Blood glucose level
BPT	Blood pressure telemonitoring
BMI	Body mass index
D(Early)	Early detection of diabetes
CGM	Continuous glucose monitoring
CSII	Continuous subcutaneous insulin delivery
CVD	Cardiovascular disease
CPCSSN	Canadian Primary Care Sentinel Surveillance Network
CPR	Cardiopulmonary resuscitation
C + S	Clinical and sociodemographic data
DL	Deep learning
DNN	Deep neural network
DTs	Diabetes technologies
DT	Decision tree
ECG	Electrocardiography
Echo	Echocardiography
EHR	Electronic health record
EMR	Electronic medical record
FDA	Fisher's discriminant analysis
G	Gradient boost
GP	Gaussian process
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability Accountability Act
HBCSSs	Health behavior change support systems
HL7	Health Level Seven International
HPM	Hybrid prediction mode
MLP	Multilayer perceptron
MA	Moving average
LDA	Linear discriminant analysis
LR	Logistic regression
LSTM	Long short-term memory
ML	Machine learning
MetS	Metabolic syndrome
NB	Naive Bayes
NGO	Non-governmental organizations
OSA	Obstructive sleep apnea
PAH	Pulmonary artery hypertension
PH	Pulmonary hypertension
PPG	Photoplethysmography
P(risk)	Prediction of risk factors of diabetes

PIDD	Pima Indian Diabetes Database
RLS	Restless leg syndrome
ROC	Receiver operating characteristics
SMOTE	Synthetic minority over-sampling technique
SVM	Support vector machine
T1DM	Type 1 diabetes mellitus
WHO	World Health Organization
XGB	Extreme gradient boost

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