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Systematic Review of Data Mining Applications in Patient-Centered Mobile-Based Information Systems

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Objectives: Smartphones represent a promising technology for patient-centered healthcare. It is claimed that data mining techniques have improved mobile apps to address patients' needs at subgroup and individual levels. This study reviewed the current literature regarding data mining applications in patient-centered mobile-based information systems. **Methods:** We systematically searched PubMed, Scopus, and Web of Science for original studies reported from 2014 to 2016. After screening 226 records at the title/abstract level, the full texts of 92 relevant papers were retrieved and checked against inclusion criteria. Finally, 30 papers were included in this study and reviewed. **Results:** Data mining techniques have been reported in development of mobile health apps for three main purposes: data analysis for follow-up and monitoring, early diagnosis and detection for screening purpose, classification/prediction of outcomes, and risk calculation (n = 27); data collection (n = 3); and provision of recommendations (n = 2). The most accurate and frequently applied data mining method was support vector machine; however, decision tree has shown superior performance to enhance mobile apps applied for patients' self-management. **Conclusions:** Embedded data-mining-based feature in mobile apps, such as case detection, prediction/classification, risk estimation, or collection of patient data, particularly during self-management, would save, apply, and analyze patient data during and after care. More intelligent methods, such as artificial neural networks, fuzzy logic, and genetic algorithms, and even the hybrid methods may result in more patients-centered recommendations, providing education, guidance, alerts, and awareness of personalized output.

Keywords: Data Mining, Patient Care, Mobile Health, Information System, Artificial Intelligence

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I. Introduction

Patients with chronic illness are constantly faced with decisions that affect their health, and the result of each decision may influence their condition. Tools to support decision-making are often based on facts and skills. There are many resources obtainable to assist patients with self-management. Training patients to recognize, evaluate, and use these resources is a part of self-management care. Skills are worthless if patients cannot move towards health improvement on a continuous basis. Taking action involves readiness to change, adequate information, goal setting, and continuing support for modification [1]. These tasks are attainable through mobile health applications. Actually, with the rapid expansion of mobile phone technology, there have been rapid advances in the development of mobile-health applications (apps). Studies have shown that users are eager to apply mobile technology for health management [1]. Mobile applications are thus considered very useful for supporting patient-centered care by facilitating various types of patient and physician interaction, and for providing greater access to information. Significantly, the mobility of these interventions is the key to permit patients to participate in their own care and to communicate with healthcare providers outside formal consultations [2]. Even using mobile apps can help patients' self-manage their conditions by delivering personalized training and treatment plans and by providing support to patients to allow them to monitor their own clinical data [3]. This has been achieved through applying data mining methods in the architecture of mobile apps equipped with special features, such as tracking crucial related values, prediction, estimation, detection, and so forth, which support patients' self-management [4-7]. Some of these app features are enhanced using data mining methods which are aimed toward personalized care of patients.

Data mining can be defined as the combination of machine learning algorithms, statistical analysis, artificial intelligence, and database management systems to extract hidden, previously unknown, humanly comprehensible, and potentially useful patterns, from large databases [7]. Personalized applications are defined as systems that facilitate a partnership among practitioners, patients, and their families to guarantee that procedures respect patients' requirements and preferences [8]. Data mining algorithms may be applied as the fundamental step in the overall process of patient-oriented and personalized care. It includes intelligent methods to generate data patterns, which are presented in the features of the mobile apps and improve their function. In this step, to prevent over fitting, data are divided into two sets, namely, training and testing sets. The training set is used as the guide to generate an adequate prediction model and patterns. The test set is used to validate the developed model during the last phase, which is often called evaluation [9].

Although there have been several review articles about m-health apps or the application of self-management methods and evaluation in healthcare [10], this study investigated how m-health applications can benefit from the use of data mining techniques in self-management and patient-centric care. Furthermore, there has been limited research related to big data application in the area of patient-centric care; studies have been mainly related to services rather than self-management or have focused on big data rather than data mining [11]. The objective of this study, thus, was to investigate the application of data mining techniques to improve the self-management features of mobile apps as well as their accuracy and reliability for that specific purpose. To fulfill this aim, we collected information such as application category, disease or condition type, operating system platform, and data mining techniques.

II. Methods

A review of data mining technique usage for patient-centered application was conducted following the preferred approach to reporting items for systematic review and meta-

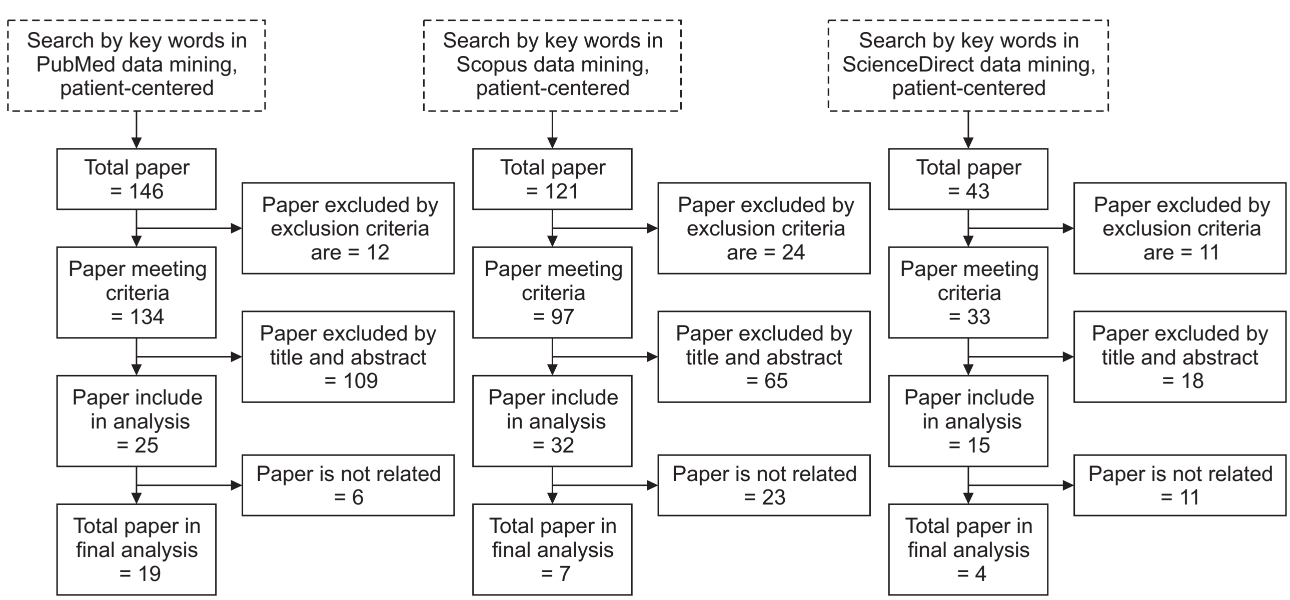

Figure 1. Process of PRISMA for data collection and analysis.

analysis proposed by Moher et al. [12]. Figure 1 shows the process of PRISMA for data collection and analysis. Different phases of systematic review are displayed in PRISMA flow diagram. Figure 1 shows the course of information collection and analysis.

Table 1. List of studied papers and their specific characteristics, including author/year, task and applied data mining techniques

Study	Year	Accuracy (%)	Task	Data mining technique
Gatuha and Jiang [14]	2016	96.4	Predicting	Naive Bayes
Tai and Lin [15]	2015	Not mentioned	Predicting	Data mining techniques
Salama and Shawish [17]	2014	Not mentioned	Follow-up	Data mining techniques
Graca et al. [18]	2014	87.5 ± 23.05	Gathering data	Data mining techniques
Shahin et al. [9]	2014	99.9	Estimation	DRSAR with multi classifier random forest
Tragopoulou et al. [19]	2014	92.81	Collecting and estimation	Movement classification algorithms and trajectory pattern analysis technique
Su et al. [20]	2014	Not mentioned	Predicting	Recognition algorithms
Rani et al. [21]	2012	Not mentioned	Monitoring	Genetic algorithm and the clustering
Andrade et al. [22]	2012	Not mentioned	Monitoring	Data mining and machine learning techniques
Tartarisco et al. [23]	2012	90.5	Monitoring	Autoregressive model, artificial neural networks and fuzzy
Sufi and Khalil [24]	2011	97	Classification	Expectation maximization-based clustering
Zhang et al. [25]	2014	0.84 ± 0.0242	Predicting	k-Nearest neighbor algorithm
Wu et al. [26]	2014	88.0	Detecting	Decision tree algorithms
Kailas et al. [27]	2012	Not mentioned	Monitoring	Probabilistic and non-probabilistic
Sefen et al. [29]	2016	87 ± 2.4	Recognizing	Naive Bayes
Pham [30]	2016	91	Monitoring	Gaussian mixture model and universal background model
Jung and Chung [31]	2016	Not mentioned	Recognizing	Knowledge-based context-aware modeling,
Zhou et al. [32]	2015	Not mentioned	Monitoring	Deep learning algorithm
Zhang et al. [33]	2015	85	Recognizing	Hierarchical segmentation
Wan Ahmad et al. [34]	2015	>0.90	Classification	Gaussian derivatives filter with seven orientations, combined with FCM clustering
Sowjanya et al. [16]	2015	99.99	Predicting	DT classifier
Pouladzadeh et al. [35]	2015	99.79	Detecting	Cloud-based SVM
Nikolaiev and Timoshenko [36]	2015	89	Monitoring	New intelligent sensors and machine learning methods
McGlothlin et al. [37]	2015	95	Detecting	Data mining techniques
Lopez-Guede et al. [38]	2015	81.80	Detecting	Data mining techniques
Menshawy et al. [39]	2015	Not mentioned	Detecting	Selection algorithms in terms of redundant features, execution time and classification
Behar et al. [40]	2015	92.2	Sleep disorder	SVM classifier
Sterling et al. [41]	2014	Not mentioned	Monitoring	Hidden Markov model
Pouladzadeh et al. [42]	2014	90	Monitoring	SVM
Sun et al. [43]	2011	97.7	Detecting	Data mining techniques

Values are presented as mean ± standard deviation.
DRSAR: dynamic rough sets attribute reduction, FCM: fuzzy C-means, DT: decision tree, SVM: support vector machine.

1. Research Question

The aim of this work was to find out how data mining techniques can be employed to improve patient-centered mobile apps.

2. Inclusion Criteria

Papers included in this study were original papers on the use of smartphone apps for patient-centered healthcare. Non-English papers were excluded as well as those for which the full-text was not available, or those that were any type of publication other than original papers (conference abstracts, review papers, letters, etc.).

3. Search Strategy

PubMed, Scopus, and ScienceDirect were the databases searched in this work. The review was performed from April 20 to June 15, 2017. The PICO criteria were used to define the search string: population [13], intervention [13], comparison (C) and outcome (O) [13]. The population was self-management application, the intervention was patient-centered application; the comparison was excluded; and outcomes were all papers that used data mining techniques for patient-centered applications. We reviewed articles published from 2010 to 2016.

4. Selection Process

Relevant papers were selected by title and abstract and were thoroughly screened by three experts. The experts extracted paper information in seven categories, including author, year, task, accuracy, and data mining techniques. Table 1 shows relevant papers and their characteristics based on study-specific aims [9,14-43].

III. Results

Based on the study search terms, 30 articles were reviewed in detail. Table 1 displays the breakdown of article categories. The features obtained from the studied apps enhanced by data mining methods were categorized as follows: 'monitoring' was the most common usages category (25%); 'predicting' (21.87%), 'detecting' (18.5%), 'calculating' (12.5%), 'classification' (9.37), 'data-gathering' (6.25%), and recommendation and follow-up (3.12%). The apps are described by features connected to the platform and patient condition/disease in Table 1. All of the reviewed articles dealt with apps that operate in 1 of 5 platforms.

As shown in Table 1, in 20 of the 30 reviewed papers, the accuracy of an applied data mining method for the purpose of patient self-management was mentioned. Thirteen of those 20 papers [4] reported accuracy of 90% or more, while 7 of those 20 (35%) reported more than 95% accuracy regarding data mining algorithms performance in the given features embedded in the mobile apps. These successful methods were mainly cloud-based support vector machine (SVM, n = 1; 99% accuracy), decision tree (n = 4; 95% accuracy), and naïve Bayesian (n = 1; 92% accuracy) with highest levels of accuracy. Overall, 16 data mining methods have been reported to be applied in mobile app design, varying from only the application of a 'genetic algorithm' for 'monitoring' to the application of multiple methods for the enhancement of one or more features. For instance, to improve 'detection', 'monitoring', and 'prediction' as features of self-management apps, the application of 7, 6, and 3 differ-

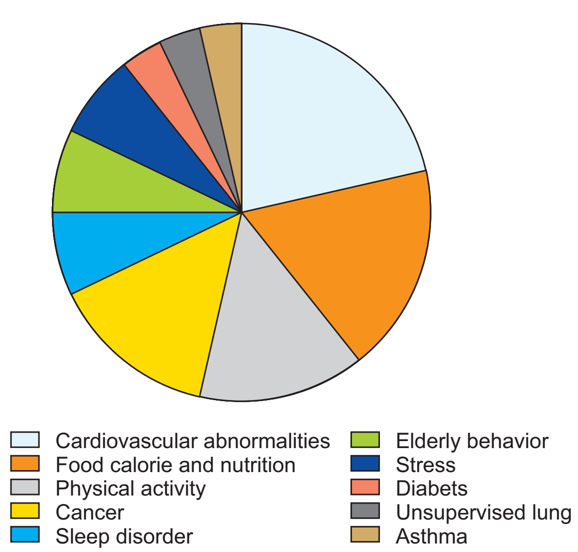

Figure 2. Distribution of illnesses covered by mobile applications improved by various data mining methods.

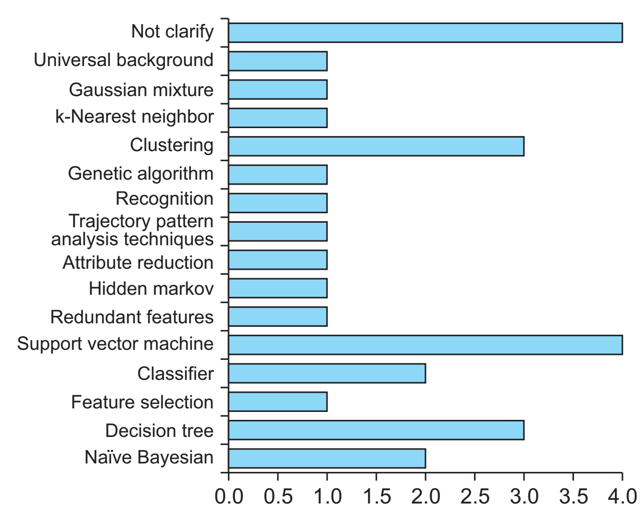

Figure 3. Frequency of data mining methods enhancing mobile application mainly used for patient self-management.

Table 2. Table of mobile application category, corresponding diseases/conditions and applied development platform

Application category	Disease/condition	Platform			
		Mobile	Cloud computing	Gadget	Sensor
Monitoring		√		√	
	Cardiac abnormalities				
	Stress				
	Self-wellness				
	Health and security				
	Physical activity				
	Colorectal cancer				
	Sleep disorder				
	Asthma				
Predicting		√	√	√	
	Malignancy				
	BMI				
	Diabetes levels				
	Motion activity				
	Dementia				
	Cardiovascular				
	Elderly behavior prediction				
Detecting		√	√	√	√
	Colorectal cancer				
	Estimate the calorific and nutrition content of foods				
	Potential CRC patients early				
	Human activities				
	Epileptic seizures				
Calculating		√	√		
	Risk level for each medical case Lebanese healthcare domain (acute appendicitis, premature birth, osteoporosis, and coronary heart disease)				
	Whole-body vibration exposures				
	Food calorie and nutrition				
Classification		√			
	Cardiovascular abnormalities				
	Unsupervised lung				
Data-gathering		√			
	Early symptoms of Parkinson's				
	Activity information				
Recommendation		√			
	Obese management				
	Elderly behavior				
Follow-up		√	√		
	Diabetes				
	Cardiac abnormalities				

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ent data mining methods was reported. The most frequently applied data mining method with the highest level of performance was SVM for the enhancement of 4 features, namely, 'monitoring', 'detection', 'calculation', and 'data gathering' with more than 99% accuracy.

As shown in Figure 2, 6.66% of the included studies reported on cardiovascular abnormalities, food calories, and nutrition management. While 13.33% of the studies focused on apps developed for physical activity and colorectal cancer purposes, sleep disorder, elderly behavior, diabetes, and stress were the focus of only 6.66%. Only 3.33% of the studies provided information on unsupervised lung disease, asthma, Parkinson disease, and seizure disorders. Figure 2 presents the percentages of studies focusing on each illness for which mobile apps are used to support patients' self-management.

A range of data mining techniques were used in the studied apps. Figure 3 shows the frequency with which specific data mining methods appeared in the literature. Support vector machine was the most frequently used method for self-management apps. Table 2 shows the application category of the reviewed apps based on disease/condition and platform. Table 3 shows mobile apps features and theirs application categories based on data mining methods used.

IV. Discussion

Self-management care is defined as the systematic provision of training and supportive treatment by healthcare expert to improve patients' abilities and confidence in handling their own health problems, including regular progress, goal setting, and solutions [44]. Self-management involves more active participation in keeping with the realities of chronic disease, whereby responsibility for routine disease management shifts from healthcare professionals to the individual patient [45]. The most common way to provide evidence-based care through designed programs has emerged during the last decade [46]. Technology supports healthcare by offering innovative options for self-management education. Mobile phones are indispensable in people's lives and can work as a platform for diverse self-management tools [4]. Users desire a mobile platform for information and applications in addition to basic phone capability, email, and access to the internet. Many consumer health informatics tools have been developed over the last decade. As of June 2013, there were 43,689 health apps available from the Apple iTunes store alone [47].

To empower these apps through a wider range of features

Table 3. Mobile apps features and theirs application categories based on used data mining methods

Application category	Data mining methods																
	Naive Bayesian	Decision tree	Feature selection	Classifier	SVM	Redundant features	Hidden Markov	Attribute reduction	Trajectory pattern analysis techniques	Recognition	Genetic algorithm	Clustering	kNN	Fuzzy logic	Gaussian mixture	Universal background	Not clarify
Monitoring		√			√		√				√	√		√			√
Predicting	√	√											√				
Detecting	√	√		√	√	√				√		√					
Calculating					√			√							√	√	
Classification												√					√
Data-gathering			√	√	√				√								
Recommendation																	√
Follow-up																	√

SVM: support vector machine, kNN: k-nearest neighbor.

and capabilities, several data mining methods have been applied; they address many capabilities, such as prediction, estimation, detection, and so forth, for each patient individually while collecting his or her data. The results of this review suggest that decision trees and rule classifiers have an analogous operating procedure; conversely, decision trees and naïve Bayesian generally have dissimilar operational profiles [48]. Furthermore, support vector machine [35] has been used more than other techniques with better accuracy. This might be due to this method's ability to classify cases accurately. Negotiations different aspect of each algorithm are beyond the scope of article. Also, each algorithm has shown great performance in one task. It is generally agreed that SVM achieves better result when handling large amounts of data, but not big data, and continuous features. SVM algorithms achieves great results in terms of accuracy in general, speed of classification, and tolerance to redundant attributes [48]. It is a reliable classification approach that groups patients based on their data for self-management purpose. This predictive modeling method produces the most appropriative evidence-based decisions for patients [49]. As a classifying supervised-learning technique, SVM is based on the concept of a 'margin' placed on either side of a hyperplane separating two data classes. The SVM method works well even when the number of features is large with respect to the number of training instances. However, the SVM method is binary, and in the case of a multi-class problem, it must be reduced to a set of multiple binary classification problems. Besides, SVM is limitation in working with discrete data [48]; therefore, the output of the mobile apps may be restricted to classifying patients into two groups, for example, risky and non-risky. However, in personalized medicine the detection of risky cases requires every single case to be labeled rather than a group of people. Thus, we need not only to support mobile apps by big data analysis; in addition a stronger data analysis technique is needed to focus on the detection, prediction, or estimation of every single risky case.

With the pervasiveness of mobile apps use and the emergence of cloud computing technology, mobile cloud computing tools have been introduced. The integration of cloud computing into the mobile environment might be a solution to overcome obstacles related to the use of data mining methods in mobile apps performance, environment, and security [50]. Patient centered care, which has become a significant trend in healthcare and technology, has had a positive effect on patient safety, access to demographic and clinical information, and clinical decision support systems. Accessibility of data, regardless of the patient and the clinician location, has become the significant factor in both patient satisfaction and enhanced clinical results. Cloud technologies can considerably facilitate this style of health care provision [51].

Holtz and Lauckner [52] reviewed 21 articles describing studies on cellphone use for diabetes management. To establish new systems, such as smartphone apps, as services to patients, the healthcare provider should be involved. It is vitally important that healthcare sectors open up to the application of such up-to-date methods of communication to realize the self-management potential reported in our studies. Thus, researchers should focus on finding ways to utilize the mobile and patient-operated disease-management apps. The application of data mining methods in the development of mobile apps may lead to new ways of delivering healthcare to people living with chronic conditions. As a result, the role of the patient as a passive recipient of care will positively be changed to an active participant in self-management [52].

One limitation of this study was the small number of articles obtained from three databases. Another limitation is that the indicators that were evaluated and the results may not be generalizable. Future investigation are required to review big data apps, which are applied in the area of personal care rather just patient-centric care.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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