# A Clinical Decision Support System based on an Unobtrusive Mobile App

Ariella Richardson[1], Avigail Perl[1], Sapir Natan[1] and Gil Segev[2]
[1]*Lev Academic Center, Jerusalem, Israel*
[2]*BGSegev Ltd. (segevlabs.org), Jerusalem, Israel*

Keywords: Mobile Health, Digital Health, Digital Monitoring, Clinical Decision Support System (CDSS), Medical Decision Support System (MDSS), Cardiovascular Disease, Silent Disease.

Abstract: Clinical decision support systems typically rely on medical records and information collected in the doctor's office. We propose a clinical decision support system that uses data collected from patients continuously and in an unobtrusive manner. The system uses data collected from a mobile app installed on the patient's device (such as a mobile phone, smart-watch etc). The app collects data without user interference and combines it with conventional medical records. Our system uses machine learning methods to extract meaningful insights from the data. The output from the learning process is then presented to the doctor in a clear and meaningful fashion on a web based platform. This system can be used to assist effective treatment selection, enable early diagnosis, trigger alarms in case of an emergency and provide a tool for disease monitoring. We describe our clinical decision support system and directions for future work.

## 1 INTRODUCTION

Often patients visit their doctor when they feel unwell searching for a diagnosis. Doctors then try to decipher the cause of the patients feeling. However, they do not always have all the data necessary for precise diagnosis, and the data that they have is often unclear and hard to integrate. As the amount of data available for patients is vast, the need for clinical decision support systems - CDSS (also called medical decision support systems - MDSS) is great (El-Sappagh and El-Masri, 2014). CDSS have been developed for various settings and conditions. A detailed architecture for integrating electronic medical records from multiple sources is presented in (El-Sappagh and El-Masri, 2014) and (Kawamoto et al., 2005; Shibl et al., 2013) survey others. Developing a CDSS that makes a contribution to the doctors practice is complex. Many of them do not improve clinical practice, as shown by (Kawamoto et al., 2005) who present a survey of several systems and discuss parameters that correlate with improving clinical practice. Some systems are simply not accepted by practitioners, factors are described in (Shibl et al., 2013).

Alongside CDSSs, health related applications for mobile phones and smartwatches are capable of improving health monitoring and detection. The number of health related apps available is astounding, approximating 40,000 apps in 2013 (Boulos et al., 2014) and 165,000 in 2015 (Terry, 2015) and growing continuously. While CDSS are typically based on electronic medical records and targeted at assisting the practitioners, mobile apps often aim at providing feedback to the patients themselves. We propose a CDSS that collects data on a patients' mobile phone, and then uses it as input to the CDSS presented to the doctor.

Our proposed system is a CDSS that integrates traditionally documented information alongside sensor information collected by the patient app on a mobile device, such as a phone or smart-watch. The combined data is analyzed using machine learning methods and presented in a clear and meaningful fashion to the clinician. This enables assistance in making medical diagnostic decisions. The system can also be used to detect and alert the doctor or patient in case of an emergency or deterioration. An important feature of our system is that data is collected not only in the doctor's office, but also between visits. This enables performing a diagnosis based on a much more information than is typically possible with other systems. Our system overview appears in Figure 1. (patent request submitted (BGSEGEV, 2018)).

Among the surplus of medical apps, many require the users to actively interact with the application in order to achieve medical feedback, for example (Seo et al., 2015; Zhang et al., 2015; Nam et al., 2014).



Richardson, A., Perl, A., Natan, S. and Segev, G.
A Clinical Decision Support System based on an Unobtrusive Mobile App.
DOI: 10.5220/0007587001670173
In *Proceedings of the 5th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2019)*, pages 167-173
ISBN: 978-989-758-368-1

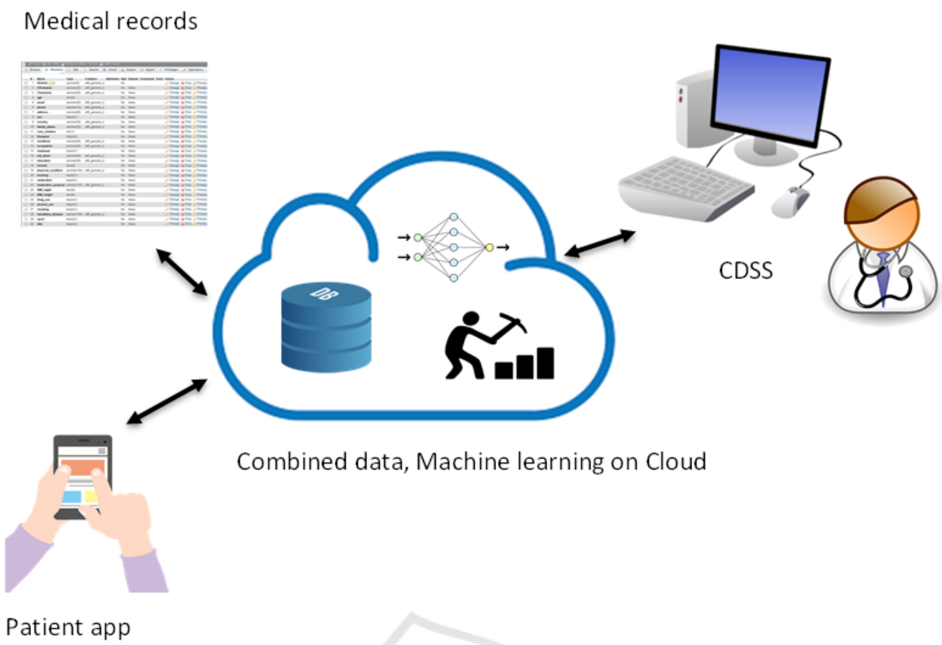


Figure 1: Overview of system.

In our system, we propose an app that will be able to provide meaningful information, without requiring user actions for data collection and input. Our CDSS works in conjunction with an application that accompanies the patient and collects data on-line using a mobile phone application. We collect data during regular phone usage, without the need for direct patient involvement. This characteristic is what makes our system different from many other health apps.

We currently focus on vascular diseases such as stroke, heart and peripheral vascular disease but have also been expanding our work to other conditions where sensor data has predictive capabilities such as cancer and osteoporosis. We collect data from many sources, for example: typing patterns, voice recordings, pulse measurements, walking patterns and injury related data.

Generally, during a doctor's visit, the doctor relies on descriptions of the patient's subjective feeling, and the patient's description of his health difficulties. These descriptions are often inadequate, and affected by recent subjective feelings, rather than unbiased, long-term and continuous health monitoring. Visits to the doctor are sporadic and often far and between due to the constraints of the health system. The physician has no way of detecting deterioration in the patient's condition between visits. Patients often visit the doctor only when the pain is unusual and sometimes this is a sign that the disease has already progressed. Our system has the benefit of being able to collect data over time and between doctor visits. The use of such data, may present a clearer picture of the patients condition than data collected periodically during doctor visits, or inexact patient descriptions of symptoms.

Moreover, the patient may not feel any symptoms of a disease. It is known, for example, that many people with PAD (Peripheral Artery disease) report a lack of symptoms, including those with a relatively serious illness (Criqui and Aboyans, 2015). With our CDSS, diseases may be detected even before the patient becomes symptomatic. Identifying diseases in an early stage is critical to treating them and may even prevent their onset, hence the great contribution of our framework. Obviously security measures must be considered when handling sensitive medical data, these are out of the scope of this study.

There is need for a system that will provide a maximal response to all of its needs without requiring active involvement from the patient during data collection. Our CDSS offers state-of-the-art management, documentation and user interface platform that receives constant feedback from the patient's application about dynamic data collected in the background and processed using data mining. Our proposed system is autonomous, and therefor reduces the number of required doctor visits, reduces human error, and enriches the medical diagnosis and monitoring process with information from new sources such as the smartphone sensors. The data mining performed in the system will provide rich output to the doctor and patient, and may also be used for real-time events and for alerting caregivers.

## 2 RELATED WORK

We consider two types of studies to be relevant to our work. The first are studies on clinical decision support systems. The second set of studies are mobile applications for healthcare, as our CDSS is heavily based on a mobile application for data collection.

CDSSs cover a broad variety of topics. Some systems are specific to a condition such as diabetes (Weymann et al., 2016) or retinal disease (Bourouis et al., 2014). Many others are aimed at assisting diagnosis based on the vast amount of medical information available. (El-Sappagh and El-Masri, 2014) present an architecture for combining electronic medical records into a single DSS to assist clinicians. A survey of CDSSs along with a detailed discussion explaining the need for such systems can be found in (Castaneda et al., 2015). Although CDSSs are plentiful, they are often slow to be accepted and do not always improve medical practice. (Shibl et al., 2013) survey several CDSS and discuss factors that impact system acceptance. One of the main parameters found to affect acceptance was whether the system interfered with the regular work-flow. Systems that required a break in the normal work-flow were not usually accepted. Surprisingly, ease of use was considered less important. Clinicians claimed that if a system was helpful they would be prepared to make an effort to use it. Other parameters are described in the paper. (Kawamoto et al., 2005) perform a similar survey to identify features that impact the success of CDSSs. They claim that clinicians were found to adopt systems, where the information was provided automatically. Clinicians were less likely to use systems that required an active search for information. Similarly, systems that used a computer to generate decision support were more effective than those that required manual intervention. The studies provide an indication, that our proposed system that requires minimal intervention on the side of the patient, and highly automated and clearly presented integrated information to the clinician, will have a high chance of acceptance.

Similar to our framework is the work by (Artikis et al., 2012). They propose a CDSS that integrates data from sensors collected on the patient, alongside other medical data, just as we do. The focus of their work is on dementia and depression, whereas we are looking at cardiovascular disease and other conditions with physical deterioration. To the best of our understanding their work was not expanded.

Another system that must be discussed in close relation to our work is that of the MobiGuide Project (Peleg et al., 2014; Peleg et al., 2017). MobiGuide focuses on arterial fibrillation, and gestational diabetes. The proposed system is targeted strongly at supplying the patient with a DSS system to help manage the disease. Although doctors also use the system, it seems that focus of this large impressive study is different to ours. We are less concerned with providing a DSS system for the patient. Our concept uses the data collected from the patient as input to the clinicians decision. Our system collects as much data as possible without inconveniencing the patient, in order to supply the doctor with as much information as possible. The information is beneficial, as it is collected between the office visits, and we hope it will assist in making a decision that is supported by long term conditions, as opposed to solely relying on recent information reported by the patient in the office.

Aside from CDSSs, it is important to consider mobile health applications that are relevant to our framework. The number of mobile applications for healthcare is vast and constantly expanding (Boulos et al., 2014; Terry, 2015). Most mobile health apps are targeted at monitoring and rehabilitation such as (Seo et al., 2015) who tested the feasibility of a mobile app for patients who had suffered a stroke. The app was aimed at managing risk factors such as blood pressure and diabetes management. Other applications (Zhang et al., 2015; Micallef et al., 2016), accompany the patient by encouraging exercises, following up on taking pills, and logging mood reports.

Some of the apps are aimed at bridging the distance between the patients to medical assistance. (Nam et al., 2014) provide a stroke screening application. The application shows a set of cartoons representing stroke symptoms. Potential patients can follow the cartoons and try to determine whether they may be suffering from a stroke. (Mitchell et al., 2011) bridge the gap by providing a teleradiology system that enables a doctor to interpret a CT scan. (Demaerschalk et al., 2012) provide high-quality video teleconferencing.

Several surveys on the use of smartphones in medicine (Ozdalga et al., 2012; Boulos et al., 2014; Dobkin and Dorsch, 2011) show how smartphones can be used for patient care, monitoring and rehabilitation alongside accessing clinical data such as electronic medical records CT scans etc. Most of these systems require active and sometimes heavy user involvement. Patients are expected to use the app frequently and enter the relevant information for data collection. We did not encounter a system that combines both of an **unobtrusive** application on the patient side with a CDSS for the doctor, in the structure of the system that we propose in this paper.

## 3 DESCRIPTION OF OUR CDSS

The main focus of this paper is the CDSS for the doctor. As shown in Figure 1 data from phone sensors is aggregated with medical history. After this data is analyzed using machine learning, a clear presentation of the output including diagnostic suggestions is displayed to the doctor. We developed a prototype web based application that presents this information to the doctor, and describe it in section 3.1. We also developed a data collection system to collect labeled data in order to train our system, described in Section 3.2.

### 3.1 CDSS

In designing the DSS for the doctor, we kept in mind that the system should be designed in a convenient and intuitive manner. Physician activity while using the system should not deviate much from regular practice, as claimed by (Shibl et al., 2013). Improvements will aim at saving time and improving diagnosis accuracy. We take User interface and experience into account in our design. The CDSS has been developed as a prototype (in Hebrew), with the actual machine learning engine left for future work.

We describe and display some of the more interesting features of our CDSS. The first feature is the disease simulator. The simulator automatically ticks boxes that the system has detected from the app data. The doctor can then discuss these choices with the patient and change the selection of symptoms. Once ticked symptoms are agreed on, the system outputs suggestions for possible diagnosis. The diagnosis output by the system takes into account both the data entered by the doctor, but also the input collected automatically by the app on the patients device. The integration of these two sets of data, both that inserted by the doctor, and that automatically collected from the patient app are what make this simulator unique. An example of what this screen looks like is shown in Figure 2. The simulator provides the doctor with a list of possible symptoms, and the doctor inputs data in a simple manner by ticking boxes. Examples to symptoms (that are ticked) are limping, slow ulcer healing, ulcers on legs and weight loss. After the aggregation with the patient app data the diagnostic suggestions are presented on the screen, and can be seen in red. For example on the this screen the proposed diagnoses are Peripheral Vascular disease (PVD) and Osteoporosis.

One of the special features in our system, is plots of the data collected by the patient app that can be viewed in real time as the data accumulates or at a later time. The doctor may choose to enter the CDSS,

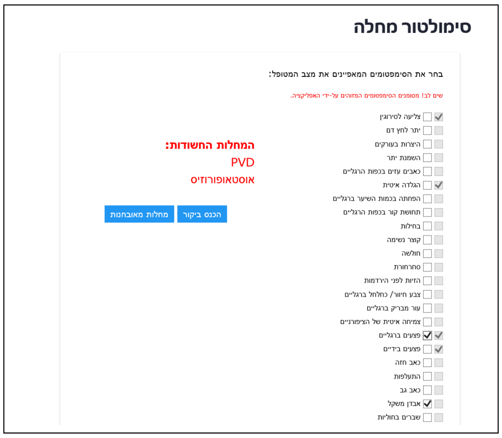


Figure 2: Diagnosis simulator. Symptoms in tic boxes, Diagnosis in red.

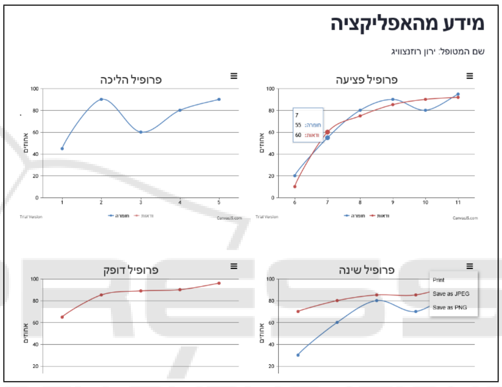


Figure 3: Plots of patient symptoms, alongside proposed diagnosis with confidence rating.

between office visits, to follow how a patient is performing. The screen displays the name of the patient, and a set of plots for graphs of ulceration information, walking patterns, pulse measurements and sleep patterns. These are all shown in Figure 3. The graphs show the patient's condition in the various profiles. The graph is accompanied by a box with the suggested diagnosis along with a degree of confidence that this diagnosis is correct. Plots can also be be printed or saved.

Alerting the doctor to suspicious events that require attention are an important part of our system. Figure 4 is the description of the profile belonging to a patient as shown to the doctor. The data includes the patient ID, age, name, phone number, address, gender etc. The data also includes medical information such as smoking habits, alcohol consumption, medications, sport, diet etc. In case of a suspicious event, an alert is displayed on the top of the screen, as shown in the figure. Then details of the patients condition can then be seen in Figure 5, that shows an example of a re-

Figure 4: Patient profile, with an alarm indicating a suspicious event.


Figure 5: Example of visit report.

port that summarizes a patients data collection. Each row has the date, type of activity performed, state detected and the suspected condition. Events that have been detected as suspicious are marked in red. Ulcers are accompanied by a picture of the ulcer.

Our system also includes standard medical system functionality such as the display of patient information in a table form, as shown in Figure 6 that describes the patients information (name, ID, visit number) Then the diagnosis, the reason for the visit, extra referrals and recommendations. Aside from the patient information, the doctor is offered links to extra reading material as shown in Figure 7, enabling access to the latest medical articles on relevant topics.

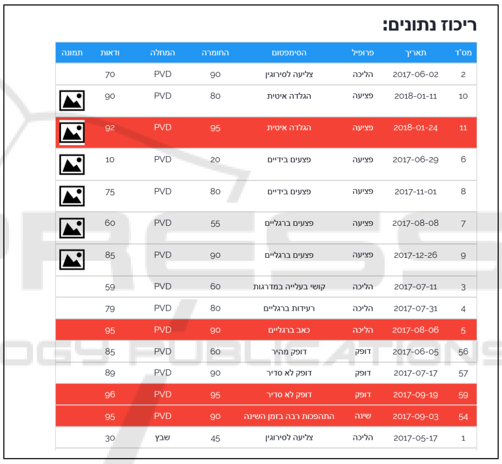

Figure 6: Patient data in tabular form, with suspicious events marked in red.

## 3.2 Labeled Data Collection

As we have stated the app used to collect patient data is unobtrusive. Data is collected without the need for user intervention. However, in order to build machine learning models we need to collect labeled data for the conditions we wish to diagnose. In order to forward our research we developed a data collection app for research. This application (that is different to the application for data collection for the CDSS) requires the user to describe the type of information being collected, and then collect the information. Examples to types of data that can be collected for research with this app are various walking activities such as running, walking and even falling, or dropping the phone. The are examples to activities that might play an important part in stroke detection. We can collect the typing patterns that are created as patients type messages or other text into the phone. We also collect voice recordings that are obtained during phone calls.

Some of the application screens are shown in Figures 8 and 9. Figure 8 shows the screen where user information is inserted. The user first defines a profile, by entering a name, gender, and age. Then the user may select a condition from a lost of conditions, such as PVD, and continues by pressing the ”continue” button on the bottom of the screen. This brings the patient to the next screen, for recording the activity. This data is used to identify the subject, as the app may be used to collect data from many subjects. Figure 9 is the screen used for recording an activity. The activity will be recorded using all sensors, and labeled according the the information provided in the first screen. First the type of activity is selected (i.e. walking, climbing stairs), then the phone position is selected, and then recording is performed by pressing the red round button, and stopped by pressing the black square button.

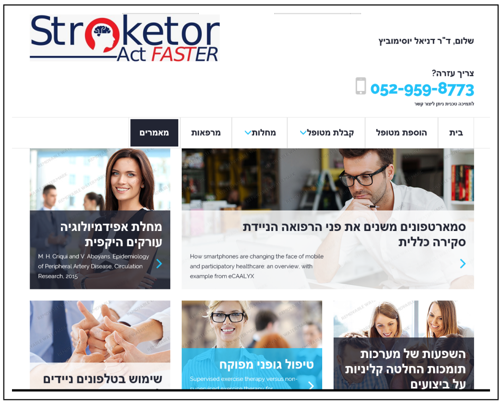


Figure 7: Extra reading material.


Figure 8: App for collecting patient information for research - subject data.

Data were collected for patients with various cardiovascular diseases: PVD, stroke, heart disease and also for osteoporosis. Early detection is a common necessity for all these diseases, and is important for the effective treatment of the disease. The ability to use the information obtained from the various sensors of the application contributes greatly to carry out the


Figure 9: App for collecting patient information for research - activity description.

disease detection. This app can easily be extended to perform data collection for research for many more conditions, and used for other research applications as well.

## 4 DISCUSSION AND FUTURE WORK

This study presents the development of an CDSS system for a doctor that works together with the patient's app. The patient app collects data from the patient, during regular phone usage, without requiring that user actively assist the data collection (but obviously with patient permission). The data is collected on the cloud and used by the doctor CDSS system to monitor and detect various diseases. It seems that the structure of the system, which combines all the information from the patient, constitutes a significant milestone in the management of the patient's medical file, to the point of identifying diseases at an early stage and even before their outbreak. The system relies on having successful data mining models, and a description of these is left for future work, as it is a separate module of the system. Using data mining to analyze the data collected in the app brings the system even further towards better disease management. In the future, we will offer research and analysis of data from other diseases, such as cancer that our team has begun to study, and adapt the system accordingly. We have begun studying various data mining methods (Richardson et al., 2019) in order to select the most appropriate models from our CDSS and will report on progress in future work. Future studies will also involve testing the system with both patient and caregiver subjects.

## REFERENCES


Artikis, A., Bamidis, P. D., Billis, A., Bratsas, C., Frantzidis, C., Karkaletsis, V., Klados, M., Konstantinidis, E., Konstantopoulos, S., Kosmopoulos, D., et al. (2012). Supporting tele-health and ai-based clinical decision making with sensor data fusion and semantic interpretation: The usefil case study. In *International workshop on artificial intelligence and NetMedicine*, page 21.

BGSEGEV (2018). BGSegev STROKETOR - stroke detector. *https://stroketor.segevlabs.org/*.

Boulos, M. N. K., Brewer, A. C., Karimkhani, C., Buller, D. B., and Dellavalle, R. P. (2014). Mobile medical and health apps: state of the art, concerns, regulatory control and certification. *Online journal of public health informatics*, 5(3):229.

Bourouis, A., Feham, M., Hossain, M. A., and Zhang, L. (2014). An intelligent mobile based decision support system for retinal disease diagnosis. *Decision Support Systems*, 59:341–350.

Castaneda, C., Nalley, K., Mannion, C., Bhattacharyya, P., Blake, P., Pecora, A., Goy, A., and Suh, K. S. (2015). Clinical decision support systems for improving diagnostic accuracy and achieving precision medicine. *Journal of clinical bioinformatics*, 5(1):4.

Criqui, M. H. and Aboyans, V. (2015). Epidemiology of peripheral artery disease. *Circulation research*, 116(9):1509–1526.

Demaerschalk, B. M., Vegunta, S., Vargas, B. B., Wu, Q., Channer, D. D., and Hentz, J. G. (2012). Reliability of real-time video smartphone for assessing national institutes of health stroke scale scores in acute stroke patients. *Stroke*, 43(12):3271–3277.

Dobkin, B. H. and Dorsch, A. (2011). The promise of mhealth: daily activity monitoring and outcome assessments by wearable sensors. *Neurorehabilitation and neural repair*, 25(9):788–798.

El-Sappagh, S. H. and El-Masri, S. (2014). A distributed clinical decision support system architecture. *Journal of King Saud University-Computer and Information Sciences*, 26(1):69–78.

Kawamoto, K., Houlihan, C. A., Balas, E. A., and Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. *Bmj*, 330(7494):765.

Micallef, N., Baillie, L., and Uzor, S. (2016). Time to exercise!: an aide-memoire stroke app for post-stroke arm rehabilitation. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services*, pages 112–123. ACM.

Mitchell, J. R., Sharma, P., Modi, J., Simpson, M., Thomas, M., Hill, M. D., and Goyal, M. (2011). A smartphone client-server teleradiology system for primary diagnosis of acute stroke. *Journal of medical Internet research*, 13(2).

Nam, H. S., Heo, J., Kim, J., Kim, Y. D., Song, T. J., Park, E., and Heo, J. H. (2014). Development of smartphone application that aids stroke screening and identifying nearby acute stroke care hospitals. *Yonsei medical journal*, 55(1):25–29.

Ozdalga, E., Ozdalga, A., and Ahuja, N. (2012). The smartphone in medicine: a review of current and potential use among physicians and students. *Journal of medical Internet research*, 14(5).

Peleg, M., Shahar, Y., and Quaglini, S. (2014). Making healthcare more accessible, better, faster, and cheaper: the mobiguide project. *European Journal of ePractice: Issue on Mobile eHealth*, 20:5–20.

Peleg, M., Shahar, Y., Quaglini, S., Broens, T., Budasu, R., Fung, N., Fux, A., García-Sáez, G., Goldstein, A., González-Ferrer, A., et al. (2017). Assessment of a personalized and distributed patient guidance system. *International journal of medical informatics*, 101:108–130.

Richardson, A., Shani Ben Ari, and Sinai, M., Atsmon, A., Conley, E. S., Gat, Y., and Segev, G. (2019). Mobile applications for stroke: A survey and a speech classification approach. In *ICT4AWE*, page to appear.

Seo, W.-K., Kang, J., Jeon, M., Lee, K., Lee, S., Kim, J. H., Oh, K., and Koh, S.-B. (2015). Feasibility of using a mobile application for the monitoring and management of stroke-associated risk factors. *Journal of Clinical Neurology*, 11(2):142–148.

Shibl, R., Lawley, M., and Debuse, J. (2013). Factors influencing decision support system acceptance. *Decision Support Systems*, 54(2):953–961.

Terry, K. (2015). Number of health apps soars but use does not always follow. *Medscape Medical News*.

Weymann, N., Härter, M., and Dirmaier, J. (2016). Information and decision support needs in patients with type 2 diabetes. *Health informatics journal*, 22(1):46–59.

Zhang, M. W., Yeo, L. L., and Ho, R. C. (2015). Harnessing smartphone technologies for stroke care, rehabilitation and beyond. *BMJ innovations*, 1(4):145–150.