m-Health 2.0: New perspectives on mobile health, Machine Learning and Big Data Analytics

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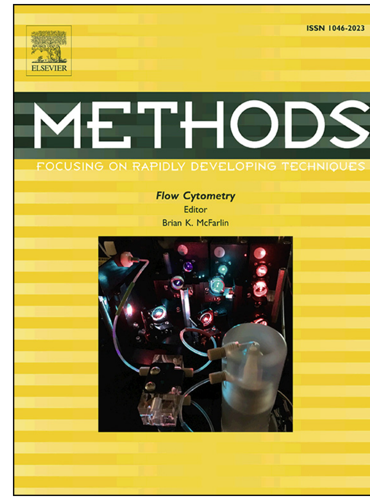

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m-Health 2.0: New perspectives on mobile health, Machine Learning and Big Data Analytics

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Abstract

Mobile health (m-Health) has been repeatedly called the biggest technological breakthrough of our modern times. Similarly, the concept of big data in the context of healthcare is considered one of the transformative drivers for intelligent healthcare delivery systems. In recent years, big data has become increasingly synonymous with mobile health, however key challenges of 'Big Data and mobile health', remain largely untackled. This is becoming particularly important with the continued deluge of the structured and unstructured data sets generated on daily basis from the proliferation of mobile health applications within different healthcare systems and products globally.

The aim of this paper is of twofold. First we present the relevant big data issues from the mobile health (m-Health) perspective. In particular we discuss these issues from the technological areas and building blocks (communications, sensors and computing) of mobile health and the newly defined (m-Health 2.0) concept. The second objective is to present the relevant rapprochement issues of big m-Health data analytics with m-Health. Further, we also present the current and future roles of machine and deep learning within the current smart phone centric m-health model.

The critical balance between these two important areas will depend on how different stakeholder from patients, clinicians, healthcare providers, medical and m-health market businesses and regulators will perceive these developments. These new perspectives are essential for better understanding the fine balance between the new insights of how intelligent and connected the future mobile health systems will look like and the inherent risks and clinical complexities associated with the big data sets and analytical tools used in these systems. These topics will be subject for extensive work and investigations in the foreseeable future for the areas of data analytics, computational and artificial intelligence methods applied for mobile health.

Introduction

Mobile health (m-Health) is considered one of the most transformative drivers for healthcare delivery innovations in modern times and has been repeatedly called the biggest technological breakthrough of our modern times [1]. In recent years, big data has become increasingly synonymous with mobile health, however the key challenges of 'Big Data and mobile health', remains largely untackled. This is becoming particularly important with the deluge of the structured and unstructured data sets produced from the numerous mobile health systems globally. With both m-Health and big data becoming increasingly popular buzzwords within the global healthcare market communities, there is still lack of proper understanding of the most appropriate computational and analytical framework and tools required for this rapprochement, considering the rapid technological developments of the former with the challenges associated with the applications and untilisation of the latter. The global usage of the mobile health applications is increasing rapidly and so is the voluminous data sets generated from these and other smart connected devices leading to complex, voluminous and multi-dimensional mobile health data that are collected and stored globally on explosive levels. This game-changing trend is largely propelled by the unprecedented global usage of the Internet connected devices, and the massive amounts of smart phone data generated by services and applications linked to these devices. As a consequence, there is major push on how to better manage, optimise and analyze this volume of data. Also, and more importantly how to convert these into meaningful information that can benefit patients, clinicians and other stakeholders. The recent developments from major corporations of the likes Apple (HealthKit), Google (DeepMind), Microsoft towards developing smarter mobile healthcare systems are evident of these trends.

To understand this further, it is essential to illustrate the original and basic structure of m-Health. Mobile health (m-Health) was first defined as '*mobile computing, medical sensors and communication technologies for healthcare*' [2]. It has evolved since then into a major global healthcare delivery innovation and technological area albeit mostly driven by successful business and market sectors. It is still aiming to reach the tipping point from the healthcare delivery efficiency and efficacy aspects and for large scale clinical adoption [2,4,5]. This rapid popularity is mainly driven by the fast innovative developments of the three technological pillars on m-Health: telecommunications, computing and medical sensing as shown in Fig. 1[2]. Billions of smart phones and Internet connected devices connected to tens of thousands of mobile health applications (Apps) are used worldwide by patients, clinicians and healthcare providers. These are continuously generating deluge of structured and unstructured datasets that are disclosing new healthcare insight opportunities but also producing challenges. The rapprochement between m-Health and big data is not new or surprisingly incidental, considering that big data science falls within the original computing pillar represented in one of the technological pillars of m-Health shown in Fig.1

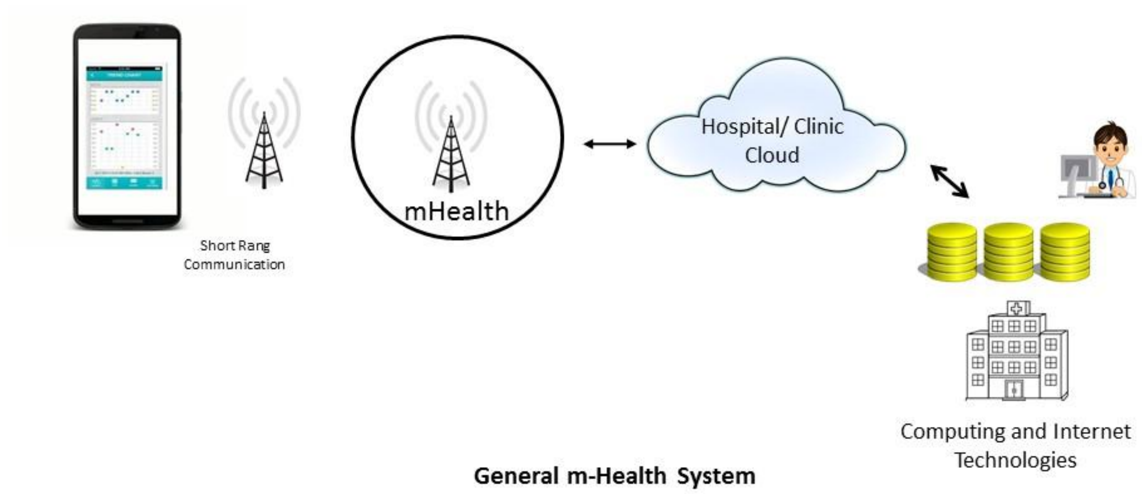

Fig. [1] The Basic building blocks of m-Health [Adapted from Istepanian etal., 2004, 2017]

The transformative technological leap associated with the introduction of the first smart phone more than a decade ago had a major if albeit controversial impact on the evolution of m-Health. This technological breakthrough allowed the inevitable amalgamation of the three building technological pillars into a single and unifying smart communications device. This also enabled powerful computational tools to be embedded within the smart phones and other devices (e.g. smart watches, wearable monitors) to generate massive and ubiquitous mobile health data sets.

This innovation step also propelled the dawn of the 'smart phone centric m-Health' era with the patient centric approach becoming the focal point of this model [2]. Today, smart phone m-Health applications (Apps) are increasingly connected to variety of wearable sensors and Internet of Things (IOT) device in variety of healthcare applications [2,3,12]. These are also becoming increasingly pervasive in every day health, wellness and clinical areas and other healthcare applications. These include for example smart cardiovascular mobile health monitors that are clinically validated as heart monitors used to monitor, diagnose and alert heart patients. Others used for the monitoring and management of diabetic patients by continuously monitoring their blood glucose levels or insulin intakes [2]. Today, these m-Health apps are exceeding the 200,000 barrier listed on the main smart phone markets with increasing trend that seems unstoppable not at least in the foreseeable future. These applications are increasingly transforming current big data repositories from their care episodes to more effective and smarter repositories for preventive approaches applied for different diseases. However, this progress is also fuelling the challenges and risks associated with the big data sets generated from these applications and devices on daily basis. Yet, this data is often either incomplete or unavailable to the healthcare providers, patients and other beneficiaries and remains largely meaningless to the most.

The capability of future mobile health systems to translate and successfully transform this lack of actionable data to a meaningful one remains one of the key challenges in developing smarter more personalised and efficient m-Health delivery systems. This new 'big m-Health data' science include the structured and unstructured data sources generated from these systems not only within the human body but also within the wider spectrum of the human health determinants; namely genetics, body, behaviour, social and society levels [6, 11]. This deluge of big m-Health data is also fuelling serious concerns and unmasking the dark side of big data with its bad and ugly characteristics [7]. These include in addition to privacy issues and security threats, the appropriate clinical data base design and data extraction complexities, the accuracy of big data statistical and analytical approaches in different clinical setting and many others.

m-Health 2.0 and big data

Big data are generally categorised into two types [2]:

(i) Structured data: These generally refer to the data that has a defined length and format (numbers, dates, strings etc.) for big data. These are the data generated by sources such computers, mobile phone, sensors, web logs, etc. This type of data represents the minority (generally around 20% of the total data generated). Examples of structured health data include data extracted from EPR, EHR, home monitoring and treatment data, medical prescriptions, etc.

(ii) Unstructured data: This generally refers to the data that does not follow a specified format for the big data, and represents the majority of the data being generated from different sources, such as general data from social media, mobile data, video and web content. Examples of unstructured health data include: social health data (e.g. tweets, Facebook, blogs), clinical notes, medication diaries and instructions etc.

From the healthcare perspective, there is still ongoing debate on the importance and impact of big data on healthcare in general and on digital health in particular. This debate is timely and important for mobile health, especially with the forthcoming introduction of the Fifth Generation (5G) mobile communications systems and their Internet-of-Things (IOT) connected ecosystems in post 2020 [8]. It is expected that billions of smart devices and phones will be connected in variety of wireless networks structures and formats and as a result of these emerging developments. Most of the wearable devices and sensors will be interconnected using these (5G) mobile networks and their compatible or derivative wireless technologies. These will also be supplemented by the immanent introduction of new generation of smart wearable sensing devices related to variety of mobile health applications [12].

From the big data and health perspectives, there are large number of clinical and non-clinical data sets that are generated from the multiple healthcare areas, these includes for example [9, 10]:

- Diagnosis, treatment and follow-up of human disease.
- Mental health.
- Environmental health.

- Nutrition.
- Social health.
- Personal (Quantified Self) health.
- Accident and safety health.
- Improving healthcare quality and reducing cost

However, from the m-Health perspective, there are many challenges that remain untackled. Some of these challenges include:

(i) Better understanding of the structured and unstructured data sources generated from the variety of future mobile and information sources post 2020.

(ii) Smart adaptation and translation of the big health data from 5G mobile health users to match the much talked about intelligent and personalised behavioural change or persuasion tools to motivate larger users and patients for their health or wellbeing improvement.

(iii) The accurate correlation between the individualised genomic data sequencing data with other wellness and health related data factors such as environment, diet, lifestyle big data and the corresponding developments in data analytics methods applied for early predisposition to genetically related diseases such as cancer, diabetes and others.

(v) Robust, accurate and secure data analytical methods for the interpretation of large medical imaging and other relevant diagnostic and imaging data generated and transmitted from the next generation of mobile imaging devices.

In order to better understand these challenges, the role of the three m-health technological pillars shown in Fig.1 need to be clarified first, particularly from the evolutionary concept (m-Health 2.0).

m-Health 2.0 was defined as' as *the convergence of m-Health with emerging developments in smart sensors, 5G communications systems with the functional capabilities of Web 2.0, cloud computing, and social networking technologies, toward personalized patient-centered healthcare delivery services*' [2,8]. The basic representation of m-Health 2.0 is shown in Fig. 2. This concept embraces an evolution of the original m-Health concept and its constituent technological principles [2]:

- Smarter m-Health sensing, driven by advances in wearable and other emerging medical sensing technologies, as described earlier. These developments represent the evolution of the original sensors' building block.
- Future mobile communications and wireless connectivity, notably 5G mobile communication systems and the associated Internet of Things (IoT) connected devices ecosystems. These developments represent the evolution of mobile communications and wireless connectivity.
- Internet-centered computing, which represents the evolution of the original mobile computing principle by adopting the functional capacities of machine learning and artificial intelligence, Web 2.0 (and beyond), cloud computing and other future computational approaches.

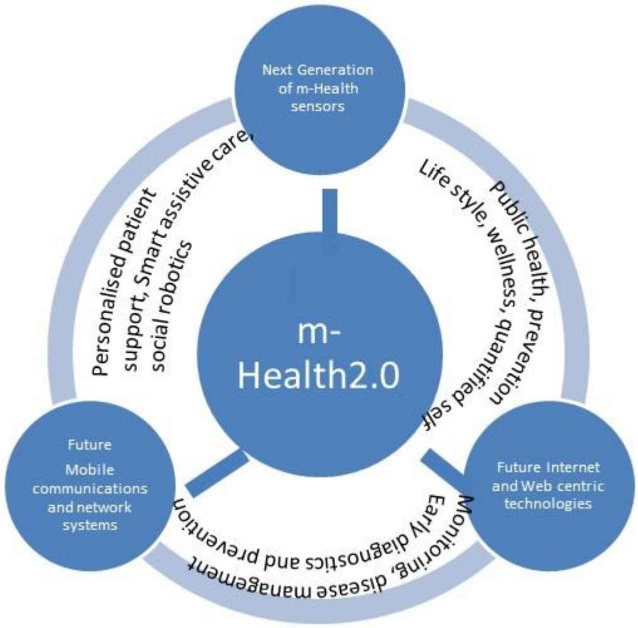

Fig. 2 m-Health 2.0: The evolution of mobile health (Adapted from [2])

This new m-Health concept representation and its enabling technologies will be the catalyst of the 'big m-health 2.0 data' sources generated from the variety of future mobile health ecosystems built around this principle especially in post 2020. This new m-Health outlook particularly from big data perspective will ultimately create new opportunities and challenges from the clinical, market and technological areas that are different from the existing m-Health models. The emerging big m-Health data types and characteristics relevant to m-Health2.0 can be categorised into three main streams:

1- **Thriving big m-Health data**: This will be the type of data generated and characterised from the vast volume of data from areas like smart health apps, quantified self, mobile health patient centric data (m-PGD) or the data from social media, smart behavioural change applications, mobile medical imaging applications and mobile diagnostic medical video streaming applications and others.

2- **Accelerating big m-health data**: This will be the type of the m-Health data generated and characterised from the systems developed around the forthcoming high speed and personalised (5G) and IOT connected m-Health devices.

3- **Diversifying big m-Health data:** This will be the type of m-Health data generated from different types of the structured and unstructured m-Health data sources relevant to m-health. These include medical and prescriptions notes, assistive home monitoring, medical robotics, smart meters and others areas related to health within the digital smart cities landscape.

The usefulness of this classification is to streamlines the big data streams with the appropriate analytical approaches that can be applied for future m-Health applications and services based on their specific data sets and types from this categorisation. These can also provide better understanding of the relevant knowledge requirements and the m-Health added value services associated with complexities of each healthcare application area.
This remains that the popularity of the existing m-Health smart phone centric model shown in Fig. 3, driven mainly due to the massive popularity and increase smart health 'Apps' globally. Many of the m-Health platforms built around this model can monitor and manage wide range of medical symptoms and conditions. These range from sleep patterns, heart rate and ECG monitoring, wellness activity levels, self-management and monitoring of different chronic diseases such as diabetes, heart failure, and chronic obstructive pulmonary disease (COPD) [2]. However, there is still increasing debate among clinicians as to whether this market and reimbursement driven model is more technologically novel than clinically useful. Furthermore the patient empowerment hype and how to leverage the big data from these systems for better patient outcomes is still debatable. These concerns are mainly due to the complex nature of thex data (volume, heterogeneity, multi-dimensionality) and to some extend to the inability of the existing m-Health models to successfully translate the complex data set to clinically meaningful and useful formats that are understandable by the clinicians and to the patients.

In reference to Fig 3, and from the 'sensing' pillar that represents the m-Health data sources generated from the sensors associated with this 'smart phone centric m-Health' approach that is widely perceived as the most successful mobile health model todate. However, this narrow yet largely market driven model restricts the wider scientific outlook behind the science behind m-Health as a perceived originally [2]. Future m-Health sensors will be widely applied for wide spectrum of different healthcare applications and interconnected devices using different 'Internet of m-Health Things' communication technologies (m-IOT) [2, 3, 8]. Examples of these applications include different sub-categories such as wearable and textile based sensors for monitoring different physiological and other biometric parameters. These include cardiovascular (ECG), body temperature, galvanic skin response (GSR), blood oxygen saturation-SpO2 sensors and other parameters. According to recent studies, it is predicated that by 2020 the big data generated from wearable m-health applications associated with the consumers driven health markets will be driving many of future healthcare and life sciences area [9]. The overall m-Health sensor taxonomy can be classified in following broad categories [2]:

1- Body Health and wellness monitoring
2- Diagnostic sensors
3- Prognostic and treatment sensors
4- Assistive sensors

This basic taxonomy spans most of healthcare applications and areas listed earlier and also encompass the most relevant determinants of human health that spans beyond the human body to societal and population health spheres [6,11]. Furthermore, within each of these general categories there are subcategories that constitutes the relevant source of the big m-Health data associated with that particular subcategory, these are described in more details elsewhere [2].

These categories and subcategories will be the main big m-Health data sensing sources and types considered within this context. However, other data sources from the other human health determinants and levels can also be generated from future m-Health systems.

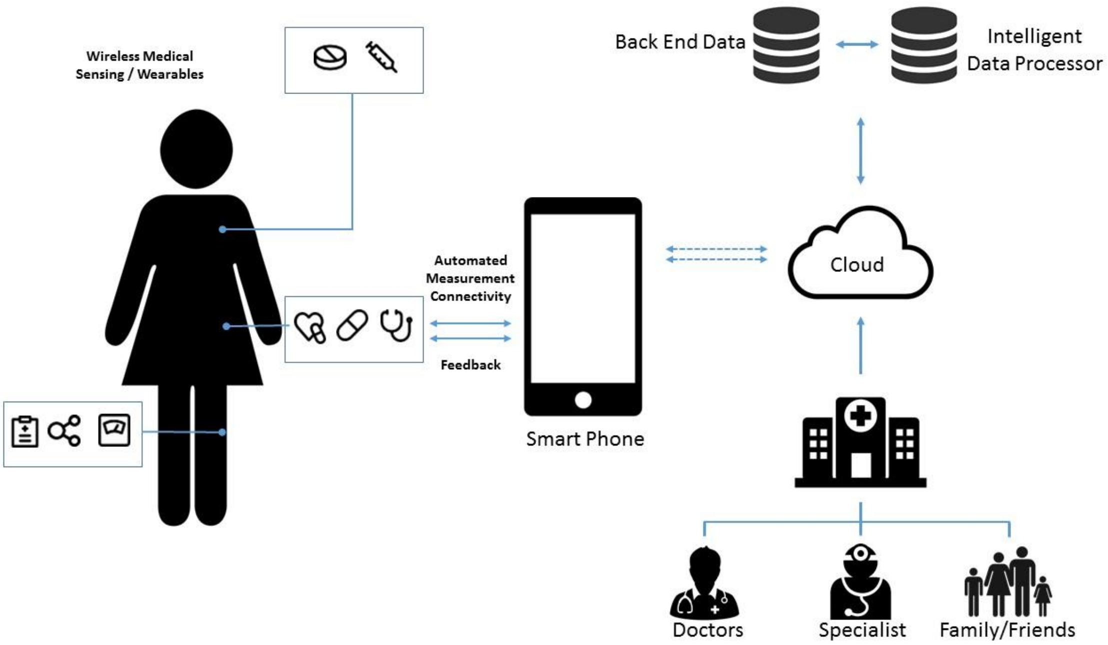

Fig. 3 The smart phone and patient centric m-Health model

From the future communications and networking pillar of m-Health 2.0 shown in Fig.2, the introduction of the Fifth generation (5G) mobile communication systems and their associated

Internet-of-Things (IOT) connected ecosystem will be catalyst for this pillar. These will provide unprecedented speed, capacity and low latency levels for mobile health applications. In summary, the (5G) mobile technologies are driven by specific requirements of data rate, latency, connected devices and expanded bandwidth capacity among others. These are summarised in the following [13]:

1- Up to 10Gbps data rate with more that 10 to 100x improvement over the current (4G) and (4.5G) networks.
2- One or less millisecond latency.
3- More than 100 X the number of the connected devices per unit area (compared with 4G LTE)
4- Up to 10-year battery life for low power connected IoT devices.
5- Coverage levels reaching 100% with nearly the same level of network availability.
6- Long batter life (Estimated by 10 years for IOT connected device to the network).

Further details of these and other (5G) technologies are descried elsewhere [13]. These characteristics and others will consequently allow an unprecedented transformation of new m-Health ecosystems that will be developed around these enabling technologies to better utilise the big data sets and types described earlier for more effective and improved clinical outcomes and patient care than the existing models.

However, in the current systems and technologies, that m-Health data generated from the sensors are used for transmitting the acquired data to their end points. These are mostly based either on the widely used low energy (power) Bluetooth communication technology or any of the other existing (IOT) technologies such as ZigBee and propriety (RF) communication technologies. The subsequent data are then transmitted to a remote cloud or data storage facility via either cellular or any other Wide Area Network (WAN) communication networks (e.g. WiFi) links for further data processing and analytics. The resultant data sets generated, transmitted and analysed from this model are used mainly for different m-Health applications mainly for remote monitoring and wellness purposes.

m-Health data analytics and machine learning tools

In simple terms, whilst data mining is typically concerned with sifting through the data to search for previously unrecognized patterns and trends, data analytics is mainly about breaking down such data and assessing the impact of these patterns overtime and predicting future trends. Big data analytics promise to deliver important and transformative healthcare insights. However, from the m-health perspective, there is still further work to be carried out in this important area. This lack of work is mainly due to the complex set of bottlenecks associated with the realisation of these from the m-Health perspective and the heterogeneity of available analytical and compatibility for m-Health. These can also be attributed to other factors relevant to m-health such as the latency challenges associated with the complexities of m-health systems, the absence of streamlined data oriented tools compatible with different sets of clinical requirements and healthcare objectives.

However, since the popularity of mobile health are expected to be enhanced further with the introduction of new technologies and innovations, the need of these data analytic tools will be demanding if not essentials for m-Health services.

There are generally four types of data analytical approaches used mainly for different business insight and financial sectors; these are [14]:

1- Descriptive analytics.
2- Diagnostic analytics.
3- Predictive analytics.
4- Prescriptive analytics.

Further details on these and other analytical tools are described elsewhere [14]. The complexity of these approaches varies. These are dependent on the type of the services provided and the value added contributions. From the m-Health perspective the different big m-Health data types described in the earlier section can require different data analytical tools and approaches. These depend on the associated risk complexities and the added value contributions of each application. These range from wellness monitoring to mission critical and vulnerable patient monitoring, diagnostics, intensive care and other smart clinical decision support management systems. All these healthcare examples and scenarios are of varying complexity and require data analytical tools. Figure [4] illustrate these popular analytical categories from the m-Health perspective.

The descriptive analytic tools can be basically applied to respond to healthcare scenarios responding to the '*what wellness monitoring or clinical episode happened*' question. These include examples of the analysis of wellness and diet m-Health data generated from young obese in certain population, or from diabetic patients with controlled blood glucose levels in certain geographical areas, or for the analysis of the data generated from hospitals to determine their capacity levels and patient admissions levels during an emergency flu seasons etc.

Whilst in the diagnostic approach, the historical big m-Health data can be applied to respond to questions of '*why a specific clinical episode or healthcare case had happened*'.

Examples include analysing the data from smart m-Health systems used to understand obesity related diabetes (Diabesity) or cases of pre- diabetic patients in specific population and geographical locations. These and other scenarios usually require more intelligent sensing requirements for the relevant m-Health systems used in these applications to collate and analyse past and current data in real time events.

In the third approach of predictive analytics, this can be typically applied to respond and inform to '*what clinical issues is likely to happen*'. These exploit the outcomes of the descriptive and diagnostic analytical approaches to detect tendencies, clusters and exceptions, and to predict future trends and relevant forecast issues for each medical scenario. Examples include optimising hospital readmissions by analysing their patient patterns, lifestyle and exiting conditions such as in multiple chronic diseases patients with multiple admissions and frequency patterns. These approaches and tools can assist healthcare providers in improving their value-based care and minimise their cost by These require more powerful and intelligent computational tools embedded within the m-health 2.0 systems used as shown in Fig.4.

In the prescriptive analytics approach, this is typically applied to '*prescribe to the relevant actions required to mitigate or eliminate healthcare problems and to exploit specific healthcare trends in improving patient or care outcomes* '. Examples of these include mitigating child health burdens or improving neonatal care and controlled gestational diabetes using the big m-Health data generated form m-Health 2.0 services and technologies. These require new m-Health 2.0 services that utilise most of the technological features discussed earlier. This approach can be particularly useful in developing more frugal m-Health systems for improving healthcare services in low to medium income countries (LMIC) as an exemplar for next generation of mobile health systems that are not necessarily are within the market driven models.

Some of the future challenges is how best to design and develop the most relevant analytical approaches with reconfigurable capabilities that can match the different objectives of m-Health services and balance between specific clinical risk complexities associated with particular m-Health application and its value added contribution.

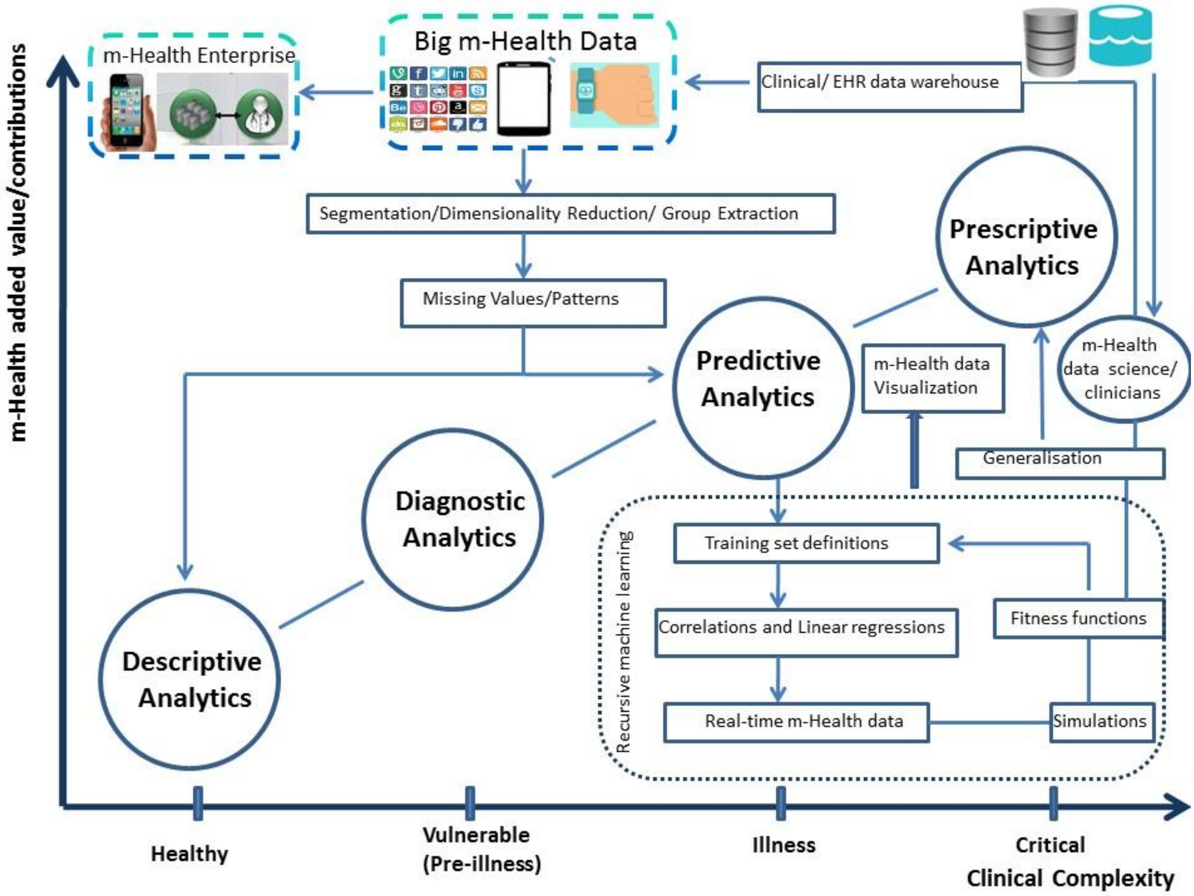

Fig. 4 m-Health data analytics and clinical complexities from the m-health perspective

From the machine learning perspective, current machine and deep learning tools and algorithms are mostly applied using the smart phone centric model shown earlier in Fig.3. It is well known that the area of machine learning (ML) is often fused with the general field of Artificial Intelligence (AI), particularly when it is relevant to the automated recognition to complex patters and making intelligent decisions based on the data. These methods include probability theory, deep learning combinational optimisation, reinforcement learning and many others. In recent years many of these machine and deep learning methods are used in different healthcare applications [15, 16]. The key drivers behind the tremendous progress in artificial intelligence within the context of m-Health data can be summarised as:

1. The decade or more of exponential growth and popularity of mobile health applications driven by the enhanced computational and power efficient capabilities inherent within the smart phone technologies.

2. The increased availability of big m-health data sets generated from smart phone applications. These are being increasingly used to train different machine learning algorithms for smarter m-health applications and services. In addition to the availability of many advanced machine learning tools with minimal programming complexities and their compatibility for such applications.

3. The unprecedented rise of global m-Health markets and their growth within recent years. This is compounded with increasing drive for developing smarter m-Health systems and ecosystems that embed or use these tools for enhanced functional capabilities.

The current taxonomy of machine learning tools applied for different m-Health services is generally either through the supervised machine learning methods (learn, identify and predict the relevant data (e.g. classification, regression techniques) or through the unsupervised methods (learn, organise and represent (e.g. clustering and dimensionality reduction techniques) of the data. These methods are usually applied for specific for each m-health application and for the patient centric model discussed earlier. More recently deep learning methods that is based on Neural Network (NN) principle, dominated new trend in machine learning approaches with many healthcare applications [16].

Many (Apps) for different clinical applications that use (AI) tools are available on the smart phone (ioS and Android) stores. Furthermore, the latest generation of smart phones are equipped with Neural Processing Unit (NPU) chipset that can provide the user with numerous intelligent functions on their own phone sets such as more accurate and instant translations, faster real time image recognition, optimised battery power handling, user's personalised social media prediction preference and many others. The era of AI chips inside the smart phone can potentially herald a new era of the (**AIm-Health**) chips. These dedicated intelligent processors will aim for personalised mobile health applications and user functionalities such as intelligent disease management, wellness monitoring, behavioural change tasks and many of the m-health themes we addressed earlier.

However, it is still imperative for all these new ideas and concept to be further studied, refined and better tailored for the targeted m-Health applications with the dual aims of : (i) closing the existing

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gap between the current m-health ecosystems and future models and applications embed with these devices (ii) The smart phone 'can never replace a doctor' concept and the human/machine intervention cannot be substituted totally by a machine.

In figure 5 we illustrate an example of smart phone centric m-Health model with a machine learning tool

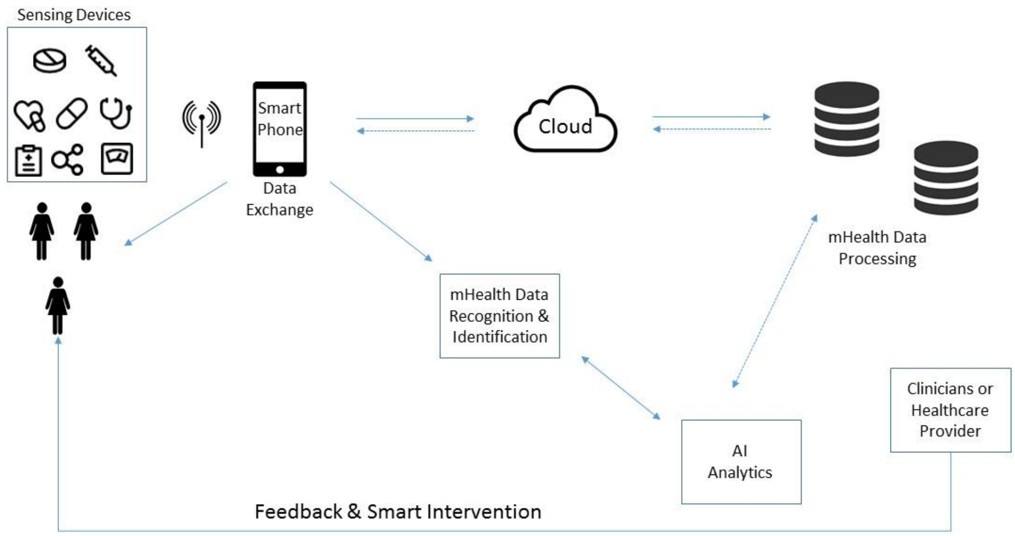

Fig. 5 A cognitive patient m-Health centric system with machine learning tools

In this system where similar m-health configurations are typically rigid and not capable of risk smart stratification with intelligent inferences for the clinical objectives. These systems can intelligently recognise, identify and tackle many of the clinical objectives required from the data sets generated from the sensors using different machine or deeps learning tools described earlier. These are can be applied for improved patient or healthcare delivery outcomes depending on the specific disease platform being managed. Furthermore, intelligent m-health system like these can also address some of the clinical risks issues associated with the multiple dimensionalities of the big data and their complexities discussed earlier to provide smart decision support systems. However many challenges on the security (data protection and application integrity) and privacy aspects (health data protection) of these mobile health models remain largely unanswered. These and other challenges can be addressed using new m-Health model discovery approaches were stipulated earlier.

Conclusions

In this paper we presented new perspectives of mobile health (m-Health) with big data analytics and machine learning. We presented the relevant big data issues from the mobile health perspective. In particular we discussed these issues from the relevant technological areas and the building blocks (communications, sensors and computing) that are associated with mobile health and the new concept of (m-Health 2.0). We also presented and discussed the rapprochement of m-Health data analytics with m-Health. The role of machine and deep learning tools within the current m-health model was also illustrated.

There is further work to be carried out especially on the larger clinical validation and efficacy issues on these systems. Major challenges remain on how to better understand the pros and cons of m-Health and how to leverage the big data originated from the forthcoming system developed around the m-Health 2.0 concept to provide better clinical benefits with meaningful care outcomes in ways that are better than the existing m-Health systems. It is also imperative to consider the big data generated from the social networking applications and tools from m-Health perspective. These include narrowing the gap between the behavioural and social determinants and potentially using analytical approaches to achieve this goal. The other challenging aspect is how to mould the big data generated from future m-Health systems that will utilise different machine learning tools to be more reactive and intelligent and to provide improved behaviour change of the patients using these systems. Other challenges and further work include development of smart frugal m-health 2.0 models and systems. In addition to the challenges related to interoperability, security, privacy and affordability of intelligent m-health products remain largely open for further work. Finally, many low to middle income countries (LMIC) countries are expected to be the next fertile grounds for frugal and affordable mobile health systems to provide better m-Health services that are much needed in the healthcare systems in these areas. The best utilisation of big data and machine learning tools in these environments remains another area for future work.

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m-Health 2.0 represent the evolution of mobile health in the era of big data analytics and machine learning innovations (big m-Health data analytics).

Several rapprochement approaches will be developed between new and smarter m-Health 2.0 applications embedded with the big data and machine learning methods.

A new cognitive patient centric m-health system with machine learning tools will be increasingly used in different mobile health applications as part of the 'digital health' evolution.

Many challenges remain in terms of privacy, security and ethical aspects. The development of 'frugal m-Health systems' targeting Low-to-Middle Income (LIMIC) countries will be important in applying these smart systems for critical healthcare delivery services and disease targets across the globe.