Creating a Learning Televillage and Automated Digital Child Health Ecosystem

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KEYWORDS

- Child health • Internet of things in pediatrics • Big data
- Artificial intelligence (AI) in pediatrics • Population child health

KEY POINTS

- Automation is posed to transform many aspects of pediatrics.
- Automated digital health with the Internet of things will allow better collection of real-world data for generation of real-world evidence to improve child health.
- Population health science allows automated digital health and potentially reduces childhood obesity.
- Real-world data and real-world evidence using artificial intelligence allows development of a learning health system leading to a sustaining digital learning ecosystem for child health.

INTRODUCTION

The fourth industrial revolution promises to transform various aspects of social interaction, including pediatric health care. Telehealth was introduced 2 decades ago and although it initially faced resistance and cost barriers, it has increasingly shown evidence of improvement. Digitalization touches almost every aspect of care, including consultations bundled with the Internet of things (IoT), to enable more effective monitoring of patients and calibration of treatment. However, large-scale evidence from robust trials is currently lacking.

Increasingly, more cost-effective wireless technologies are focusing on patient and caregiver centeredness; for example, with apps that focus on child, parent, and

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clinician interactions and chatbots that allow patients to be digitally engaged with the clinic on a continuous basis. In addition, sensors in wearables create an opportunity for digital phenotyping to potentially enable closer monitoring of child and parental health.

Data collected by new digital devices opens an avenue for mining through artificial intelligence (AI) and predictive analytics, to convert real-world data into real-world evidence. Although there are challenges of telehealth and AI in medicine, the need to integrate health and health care systems into a cohesive ecostructure to enable health care providers to constantly adapt, respond, and learn from the health ecosystem and the current expectations from modern parents is evident.

This article focuses on applying real-world data and real-world evidence by the use of population health science in automated digital health and childhood obesity. It reviews current literature and shares practice evidence from Singapore, where the currently available technologies allowed the development of a digital televillage for child health. It describes experiences with the role of clinician in automated digital health, potential uses and abuses related to the implementations of automated digital health, and the assessment of outcomes of automated digital health in childhood obesity. The article concludes by describing what a digital learning health ecosystem for child health might look like.

TELEHEALTH, AUTOMATED DIGITAL HEALTH, AND THE INTERNET OF THINGS IN PEDIATRICS

Telehealth, including telecommunications and virtual technology, can help reshape and improve delivery of child health. The different domains of telehealth include telecollaboration, teletreatment, telemonitoring, and telesupport, and the requisite standards are clearly defined by various governing authorities.[1–6]

The 'Internet-of-Things (IoT)", coined by Kevin Ashton in 1999, refers to a system of interrelated computing devices, mechanical and digital machines, objects, or people that are provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction, bridging the health care environment and the community at large.[7]

The Digital Space for Personalized Child Health

Teleconsultations

Medical consultations have been enhanced through teleconsultations, both between providers and patients and between providers (**Fig. 1**). Such consultations can be used for follow-up clinical care or for new consultations. Health care providers play an important role in the appropriate selection of patients because not every type of patient can be managed through a teleconsultation. The role of teleconsultation will continue to grow as both evidence for and confidence in this modality develop and clinicians learn more about its potential pitfalls and challenges. In the United Kingdom, Babylon Health[8,9] has introduced such teleconsultations systems. At KK Women's & Children's Hospital in Singapore, we have set up the Smart Health Video Consultation Platform (**Box 1**) for teleconsultation. The system allows for scalability across the health care sector with economies of scale, and pilot data have shown time savings per session for the teleconsultations on this platform.

Medical devices and biosensors

Besides the digitalization of analog medical devices such as the stethoscope,[10,11] as well as the increasing use of transcutaneous bilirubinometers in the monitoring of jaundice in children,[12,13] the advent of wireless devices/biosensors, particularly those that

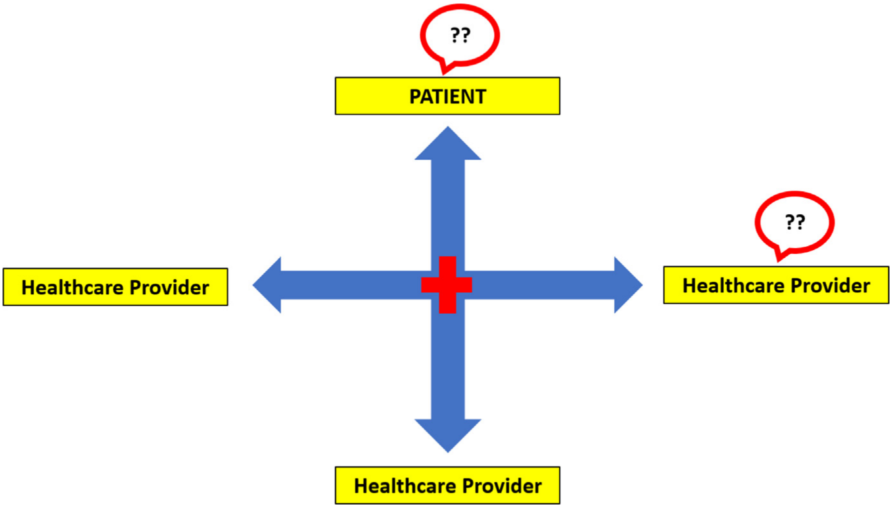

Fig. 1. Teleconsultations between health care providers/physicians and patients and between health care providers/physicians and health care providers/physicians.

monitor vital signs, electrocardiograms, glucose, and other point-of-care results, might play a pivotal role in child health in the coming years.

RAPID (Real-time Adaptive and Predictive Indicator of Deterioration) is a project from Birmingham Children's Hospital. This 3-year study funded by the UK Department of Health and the Wellcome Trust used real-time monitoring technology pioneered by McLaren from Formula One. Patch devices with wireless technology continually monitored data from patients, such as heart rate, breathing rate, and oxygen saturation.[14,15]

Biosensor wearables are becoming increasingly common and available. As consumer-grade devices such as Apple Watch and Fitbit continue to evolve with improved accuracy and integration with other digital devices and apps, many are looking toward the health care space to increase their market share. There is a growing opportunity for collaboration between the various stakeholders, such as the companies, engineers, and health care sectors, to develop clinical solutions for the assessment and treatment of patients. These wireless biosensors have a longer battery life, and many are water resistant and do not compromise patient comfort. They can monitor vital signs continually, upload the data into an analytical platform, and provide early-warning scores.[16,17] Virtual teleconsultations can be enhanced when biosensors provide real-time vital signs of the patient across the Internet to the health care provider. Algorithms can also be used to help the provider better understand the immediate care needed. In the community, patients can use these disposable wearables to monitor their medical conditions. In the future, it is reasonable to envision children with asthma putting on wearables and using predictive analytics connected to the cloud to review their real-time vital signs (ie, oxygen saturation and heart rate) and predict the severity of their asthmatic attacks, giving specific personalized and focused instructions on how to mitigate the asthma attack, including how many puffs of bronchodilators to administer and when to go to the nearest emergency department.

Social media, apps, chatbots, and digital phenotyping in child health

The health of children goes beyond the physical, mental, and psychological wellness of the individual and is connected with the community at large and influenced by

Box 1
Features of a smart health video consultation platform

Multiparty conferencing feature to facilitate a variety of health care programs and cross-institutional collaboration.

High video and audio quality and reliability, with reduced call drops over the Internet.

Leverage consumer mobile devices for ease of access.

Interoperability: caters for future integration with national health IT systems for seamless user experience.

Secure cloud-based platform: protected by proven technologies such as 2-factor authentication and end-to-end encryption.

Customer self-care portal that allows appointments to be made via e-mail and or SMS (short message service).

environmental, socioeconomic, and many other factors. The advent of the internet and cloud technology has created an interconnected and sharing community. It can be argued that the internet and social media represent the twenty-first century iteration of this ecological-environmental interconnected system. Clinicians should leverage on the social media platform as an opportunity to create a televillage to advance and improve child health. Social media are also important platforms for health care institutions and providers to provide credible and evidence-based information.

Apps can be used to help people with specific needs; for instance, children with special needs. The current cyberuniverse is rife with apps for children with these special needs.[18] It is thus important for these apps to be evaluated in a transparent and systematic manner so that health care providers are able to provide evidence-based advice for their patients.

A chatbot is a software with artificial intelligence (AI) that simulates a conversation/chat using natural language via messaging applications, Web sites, mobile apps, or through the telephone.[19] Chatbots may help in providing timely health advice for patients and families. They could address queries concerning specific diseases and escalate these queries to trained health care professionals when indicated. Caution is needed with such medical advice, and safeguards need to be put in place so that such advice is not misconstrued or misunderstood. Users should be given ways to connect with health care providers should they remain unsure of what to do after receiving such advice. Because it involves the general health and well-being (and morbidity) of children, implementation of such medical chatbots must be properly planned and evaluated before implementation. Similar to the health care apps, the postimplementation evaluation of medical chatbots should also be conducted.

A nudge, as defined by Thaler and Sunstein,[20–23] is “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives.” There are health nudges now emerging to help drive proper child health behavior toward vaccination and healthy eating.[24,25] Moving forward, smart health nudges with robust design architecture with feedback loops and machine learning (ML) to improve the nudges and customize them to the individual needs of the population should be developed and are technically achievable at this stage of the digital revolution.

As described by Jukka-Pekka Onnela,[26–28] digital phenotyping is the “moment-by-moment quantification of the individual-level human phenotype in situ using data from personal digital devices" (in particular smartphones). Although still in development, digital phenotyping can potentially be used to identify postpartum depression or significant stress or depression in teenagers, through the digital signals they emanate. Increasingly, individual and population health behavioral preferences can be monitored and collected, and these repositories of behavioral health data can help clinicians as a community when they evaluate population health science and practices and develop new approaches to shape better health for children.

In short , the use of telehealth and telecommunications from teleconsultations, and the use of wireless biosensors, apps, and chatbots, although concurrently leveraging on social media to shape pediatric health behaviors, creates much opportunity for clinicians to improve health care and population health in pediatrics. Separately, these digital technologies have limited ability to effect change in child health but, if they are integrated together, they provide greater opportunities to enhance child health. The integration of digital technologies can be made possible only through collaborative efforts between various stakeholders on an individual and population level. Ultimately, a sustainable digital learning child health ecosystem can be built using AI and ML through real world data (RWD) and evidence to continually improve child health in this televillage (**Fig. 2**).

BIG DATA, ARTIFICIAL INTELLIGENCE, AND PREDICTIVE ANALYSIS: CONVERTING REAL-WORLD DATA TO REAL-WORLD EVIDENCE

In this fourth industrial revolution, data has been called the new oil[29] and AI the new electricity. There has been an exponential increase in data analytic advances in medicine over recent years,[30] and the potential of AI becomes increasingly evident.

In medicine, RWD are the data relating to patient health status and/or the delivery of health care routinely collected from a variety of sources. RWD can come from several sources and include electronic health records (EHRs); investigations from laboratory, radiology, electrocardiogram, and other point-of-care tests, genetics, and so forth); claims and billing activities; product and disease registries, patient-generated data, including in-home use settings; and data gathered from other sources that can inform on health status, such as mobile devices, including vital signs, point-of-care tests, and behavioral health patterns. Some RWD are complex and require data mining refinement before it can be used for further analysis and for translation into real-world evidence. EHRs, with their wide, disparate information, requires data mining. Health care providers, administrators, and technology providers should work closely together to ensure that the clinically important data can be easily mined and provide building blocks for development of evidence-based health care and the integration of AI.

Data will enable the development of an evidence-driven health care system.[30] Real-world evidence (RWE) is the clinical evidence regarding the usage and potential benefits or risks derived from analysis of RWD. RWE can be generated by different study designs or analyses, including, but not limited to, randomized trials, including large simple trials, pragmatic trials, and observational prospective and/or retrospective studies.[31]

AI is "a field of science and engineering concerned with the computational understanding of what is commonly called intelligent behavior, and with the creation of artefacts that exhibit such behavior."[32–42] ML, of which deep learning is a subset, was coined in 1959 by Arthur Samuel. ML is a critical component to AI development and finds patterns in data and then predicts the outcome (**Box 2**). In essence, AI and ML are the tools that are used to analyze RWD and develop RWE and translate these

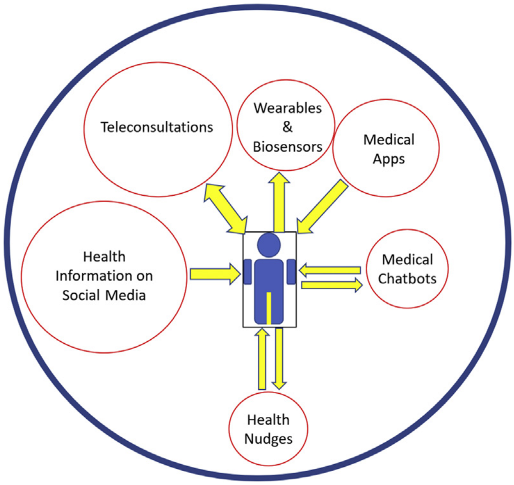

Fig. 2. The digital space for personalized child health.

into real-world algorithms for ultimate patient health care. An example of ML on the Web is Google's Deep Mind.

Kokol and colleagues[43] reviewed AI in pediatrics from a bibliometric perspective and, using a thematic analysis, identified 6 domains in the literature (Table 1). Through data-generated evidence, clinical decision-support systems (CDSSs) can be set up to improve health care delivery and health.[30] A CDDS is a health information technology system that is designed to provide physicians and other health professionals with clinical decision-making tasks. As Hayward and Neupert[30] from the Centre for Health Evidence put it: "CDDS link health observations with health knowledge to influence health choices by clinicians for improved health care." CDSSs constitute a major topic in AI in medicine.

Through ML, clinical algorithms can be set up to drive clinical decision making.[44–46] Increasingly, there are examples of this happening in clinical care. Specific pediatric examples include identifying children with autism, developing algorithms to manage pediatric sepsis, and developing a pediatric risk score that is integrated into the EHR and provides an early warning sign for clinical deterioration.[47–49]

Some RWD are complex and require data mining refinement before they can be used for further analysis and for translation into RWE. With its wide and disparate amount of information, EHR requires data mining.

Liang and colleagues[50] recently used ML classifiers to query EHRs in a manner similar to the hypothetical-deductive reasoning used by physicians and unearthed associations that previous statistical methods did not find. Their model applied an automated natural language processing system using deep learning techniques to extract clinically relevant information from EHRs. In total, 101.6 million data points from 1,362,559 pediatric patient visits presenting to a major referral center were analyzed to train and validate the framework. Their model showed high diagnostic accuracy across multiple organ systems and was comparable with experienced pediatricians in diagnosing common childhood diseases. It suggests that implementing an AI-based system as a means to aid physicians in tackling large amounts of data, augmenting diagnostic evaluations, and to provide clinical decision support in cases of diagnostic uncertainty or complexity is possible in the near future.

Box 2
Machine learning: types, models, and classification algorithms

Some common types of learning algorithms:
- Supervised learning.
- Unsupervised learning.
- Reinforcement learning.
- Feature learning.
- Sparse dictionary learning.
- Anomaly detection and association rules.
- Deep learning (or deep structured learning or hierarchical learning) is a type of ML that requires computer systems to iteratively perform calculations to determine patterns by itself based on artificial neural networks. Deep learning is essentially an autonomous, self-teaching system in which existing data are used to train algorithms to find patterns and then use that knowledge to make predictions about new data.

Various models used in performing ML (which is trained on some training data and then can process additional data to make predictions)
- Artificial neural networks
- Decision trees
- Support vector machines
- Bayesian networks
- Genetic algorithms

Types of classification algorithms in ML:
- Linear classifiers: logistic regression, naive Bayes classifier
- Nearest neighbor
- Support vector machines
- Decision trees
- Boosted trees
- Random forest
- Neural networks

Data from Refs.[35,39–41]

Challenges of Telehealth and Artificial Intelligence in Medicine

Although certain benefits are obvious, there are several challenges related to the application of telehealth and AI in pediatric medicine.

First, the sustainability of AI and the need for continuing AI learning has been recognized as a challenge. The Google Flu Trend was very promising when it was first launched in 2013 but the algorithm lost its accuracy as time wore on,[51] which shows that, although big data can play a substantial and impactful role in clinical care, clinicians must also be aware of their limitations and the potential hubris of any big data applications.[52–54] There is the need for continuous ML, akin to continuing medical education for pediatricians when new information and data are uploaded and refreshed on the existing models and algorithms set down. The IBM Watson tool was similarly touted to be the AI for new medicine but now its role has been questioned.

Second, AI and deep learning are often ultimately a “black box.” Although human beings accept the heuristics of their decision making, as AI in medicine becomes more complex, there are increasing concerns about the black box of AI or of deep learning.[55] Human beings can only process so much data and, as they try to process massive amounts of data, the relative human-to-machine decision-making effort shifts to ML. This process creates a black box in the understanding of how AI arrives at complex decisions. This outcome has also legal implications: although there are existing standards set down by the Health Insurance Portability and Accountability Act (HIPAA)

Table 1
Artificial intelligence in pediatrics: a bibliometric perspective

Theme	Applications
AI in brain mapping	Prediction of child brain maturity, brain functional connectivity in preterm infants, classifying individuals at high risk for psychosis/pediatric unipolar depression/ analysis of resting-state brain function for attention-deficit/hyperactivity disorder, predicting the language outcomes following cochlear implantation and so forth
AI use in pattern recognition	Seizure prediction in children with epilepsy; visualization of complex data[20]; predicting neurodevelopment; identifying motor abnormalities; analyzing EMG, ECG, and other signals; image analysis; segmentation; and so forth
AI use in pediatric oncology and gene profiling	Identification of regenerating bone marrow cell populations, benchmarking key genes for cancer drug development, gene expression profiling for children with neuroblastoma or lymphoblastic leukemia
AI use in developmental disorders	Quantifying risk for anxiety disorders in preschool children, developing socially intelligent robots as possible educational or therapeutic toys for children with autism, identifying children with autism based on face abnormality and so forth
AI in pediatric emergency care	Automated appendicitis risk stratification, supporting diagnostic decisions, traumatic brain injury, and detection of low-volume blood loss
ML approaches	Artificial neural networks, support vector machines, decision trees and bayesian networks

Abbreviation: EMG, electromyogram.
Data from Kokol P, Završnik J, Vošner HB. Artificial intelligence and pediatrics: A synthetic mini review. Pediatr Dimensions, 2017;2(4): 1–5.

for compliance, there are still many legal issues that need to be sorted out in this new digital frontier, especially in health data protection and security.

With regard to its infrastructure, there is much cost that needs to be invested in setting up the ongoing infrastructural needs of a digital system, related to privacy and data protection issues. The interconnectedness of the global community raises risk issues concerning personal health data security and protection, particularly if it involves sensitive health data of patients. Systems must be put in place to properly secure and protect these databases.

Recently, federated learning[56–58] has been touted as a possible solution to guard privacy and yet increase the power of AI in medicine. Computing in a smartphone is now very powerful. This power will allow dissemination learning to be done off site on handphones in a distributed but connected, integrated, and safe manner.

Federated learning is a distributed ML approach that might minimize the risks of data security and ensure data protection.

APPLYING REAL-WORLD DATA AND REAL-WORLD EVIDENCE: POPULATION HEALTH SCIENCE IN AUTOMATED DIGITAL HEALTH AND CHILDHOOD OBESITY

The health needs in pediatrics have evolved, and Palfrey and colleagues[59] identified these millennial morbidities in community pediatrics, including overweight and obesity, increasing mental health concerns, and technological influences on health.

Population health science is an emerging field in health science that takes an interdisciplinary approach to addressing problems of population health, taking into account the biological, social, and behavioral determinants of health. This approach integrates public health with social science and other disciplines, and places health as an important consideration in decisions made in all societal sectors. Such a multilevel and coordinated approach is best shown by childhood obesity, where there are marked disparities by race, socioeconomic status, neighborhood, and access to health care. A successful approach will need to take into consideration not just the biological nature of the disease but also the societal influence of policies, social environment, and physical environment to alter the physical activity and eating habits of the family and child. **Fig. 3** shows an adapted framework introduced by the US National Institutes of Health–supported Centers for Population Health and Health Disparities using childhood obesity as an example to show the proximal, intermediate, and distal factors affecting the disease.[60] A promising example will be the multilevel approach to childhood obesity in Cambridge,[61] an ethnically and socially diverse urban community, which has led to a reduction in prevalence of childhood obesity in the community. This massive collaborative effort took 7 years from formation to implementation, and sustainability and automated digital health may potentially hasten the process and allow rapid translation in more communities. Automated digital health can potentially be deployed in the various proximal, intermediate, and distal factors to affect health outcomes. Integrating a multilevel approach using automated digital health can potentially enhance population health and provide data for more proactive approaches to diseases requiring such an approach.

Role of Clinicians in Automated Digital Health

The Expert Committee on the Assessment, Prevention, and Treatment of Child and Adolescent Overweight and Obesity mentioned the role of the primary care provider in the office to diagnose and manage childhood obesity.[62] These recommendations also cite motivational interviewing as one of the behavioral strategies for physicians to assess the family's readiness for change. However, diagnosis is difficult to implement because of time constraints and the need to calculate body mass index (BMI) and plot on a gender-appropriate and age-appropriate chart. Primary care providers may not be trained in motivational interviewing and may lack confidence and time in providing feedback on a child's weight status. Primary physicians also do not have the time to do a nutritional and physical activity assessment and provide personalized feedback.

Traveras and colleagues[63] showed how a computerized, point-of-care decision alert helps alleviate the challenges discussed earlier and showed a reduction in BMI of study participants with childhood obesity. The pop-up alert includes several parts: (1) generate an automated alert on child's BMI percentile, (2) document a diagnosis of obesity, (3) discuss nutrition and physical activity, and (4) provide educational

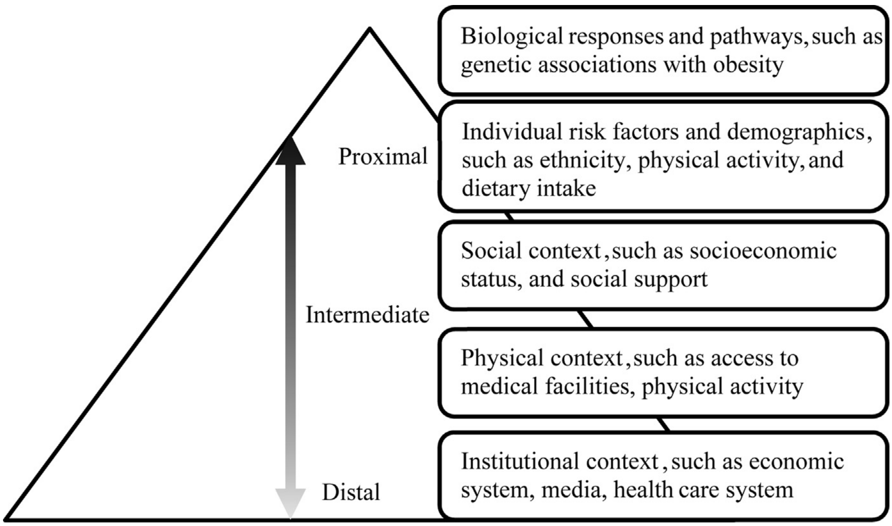

Fig. 3. Population health science model of childhood obesity that leads to disparate health outcomes.

materials. Follow-up phone coaching by health educators trained in motivational interviewing with automated text messages was also incorporated in the intervention.

With the advent of wearables, integrating tracking data with personalized feedback and prompts, as detailed earlier, is a potentially powerful tool to be used in the management of chronic diseases. Clinicians can still be an important resource in monitoring growth, providing evidence-based information, and troubleshooting in areas that families are struggling with.

Implementations of Automated Digital Health for Childhood Obesity: Its Potential Uses and Abuses

Some of the possible opportunities that automated digital health provides that are currently still under investigation include allowing the tracking of lifestyle changes; providing rapid real-time, personalized feedback and interactivity through data analytics and AI and reducing dropout rates; integrating data from wearables; and its accessibility, especially to the young.

However, with the widespread use of social media, adolescents are susceptible to cyberbullying and Internet addiction. Privacy issues are also areas that the laws struggle to catch up with internationally. With the sleep-wake cycle reversal common in adolescence, excessive social media can potentially aggravate sleep difficulties, which can lead to overweight. Clinicians will need to provide anticipatory guidance to parents to supervise their children's digital usage.

Assessing Outcomes of Automated Digital Health in Childhood Obesity

Because of differences in the types of outcome measured and how the outcomes are being measured, it is difficult to interpret the effectiveness of automated digital health. Current research is limited by standardized outcome measurements, which do not take into account the unique features of each patient.

Various policy makers, stakeholders, researchers, and clinicians need to work together to have common terminology in assessment of outcomes in childhood obesity interventions. Before accurate assessment of interventions can be performed, clinicians first need to rely on a comprehensive assessment of both the family and child with obesity. Childhood obesity is a chronic disease with medical and psychosocial complications, and assessment of just 1 parameter is insufficient. The Edmonton Obesity Staging System for Pediatrics (EOSS-P),[64] which is adapted from the adult-oriented EOSS, stratifies patients according to obesity-associated comorbidities and barriers to weight management. The EOSS-P is a potentially powerful, simple tool for assessing childhood obesity. There are 4 graded categories (0–3) within 4 main domains: metabolic, mechanical, mental health, and social milieu (the 4 Ms) to help inform physicians on a stage-based management plan. Although the EOSS-P is based on common clinical assessments that physicians perform, it will be time and resource intensive to assess the 4 domains. Automated digital health can potentially alleviate that through self-administered questionnaires and to provide the clinician with the summary of the risk category that the patient is in so that the clinician's consult can potentially be more targeted and effective.

At present, the success of childhood obesity intervention is commonly assessed using BMI z-score.[65] Other outcome measures that are commonly assessed include quality of life and cardiometabolic parameters.[66] There are several limitations to using these outcome measures. Opportunities may be missed in highlighting positive lifestyle changes that a child or family may have undertaken that may predate BMI changes.[67–71] Researchers and clinicians may be similarly discouraged because the improvement may be diluted by varying levels and domains that each child is affected by in the 4 Ms (metabolic, mechanical, mental health, and social milieu). Thus, a comprehensive, standardized, automated assessment of children with obesity can potentially provide opportunities to improve patient outcomes, experience, clinical effectiveness, and patient safety.

DEVELOPING A DIGITAL LEARNING HEALTH ECOSYSTEM FOR CHILD HEALTH

What might a digital learning health ecosystem look like? The US Institute of Medicine (now National Academy of Medicine) defines a learning health care system as one in which science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery

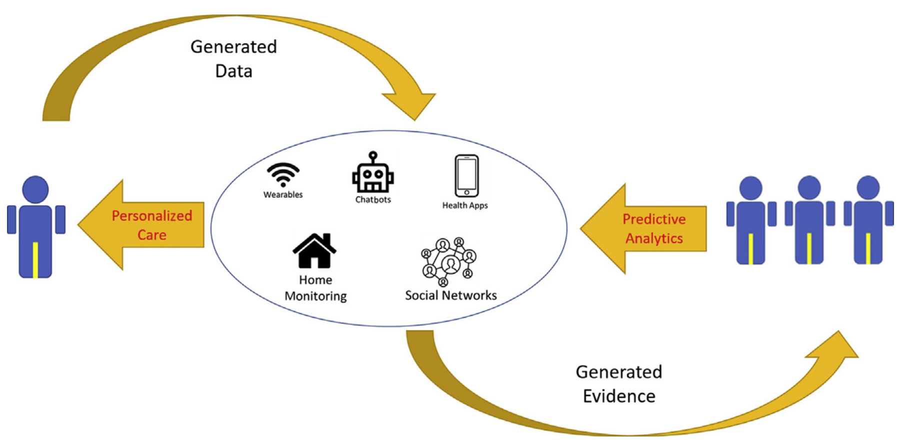

Fig. 4. Personalized care and predictive analytics for individuals and the population.

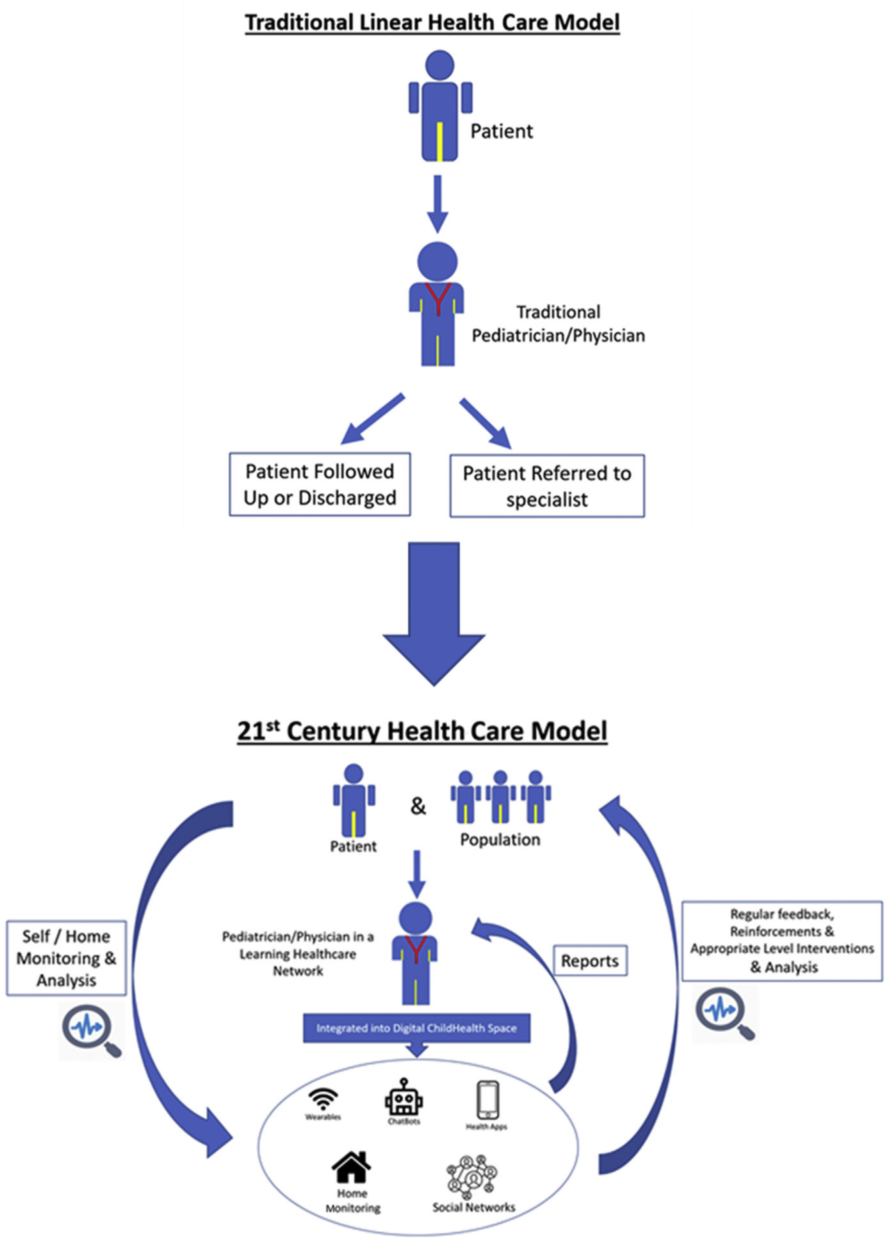

Fig. 5. The traditional linear health care model and the twenty-first century child health learning ecosystem.

process and new knowledge captured as an integral by-product of the delivery experience.

Science develops evidence that translates to care. Clinical care in turn provides RWD to develop new science, and the cycle continues. The televillage collectively involves clinicians, patients, and communities. Scientific data should be constantly

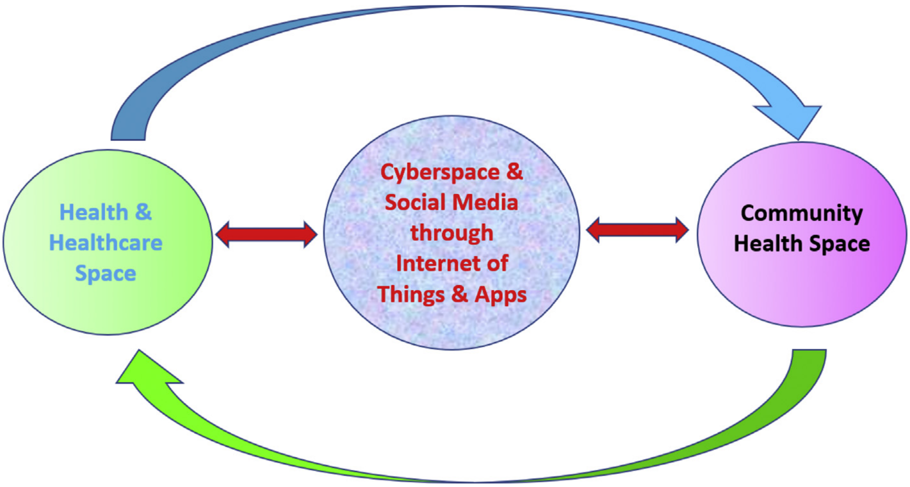

Fig. 6. Bridging the health/health care space and community health space with technology.

interrogated and translated back into practice on the ground. RWD and RWE should concurrently feed into this learning framework so that the ultimate result is an improvement in clinical care. Through technology and population study, predictive analysis can develop personalized care for individual patients. Data from individual patients will generate evidence and drive more population studies (Fig. 4).

The current health care system model is linear and, by design, wasteful, with little opportunity for learning and improving. This linear mode[68] is not set up to be a learning health care system, in which there are continuous loops of constant RWD and RWE with learning, reworking, and translation back into the real world and then back again. Technology can enable the development of a constantly learning health care system, with seamless integration of care to meet the core elements of a learning health ecosystem, transforming clinical care from the current wasteful linear model to one that is continuous and constantly learning and improving (Fig. 5). Technology will move the population health management from one that is hospital-centric to one that is village life–centric, where patients and population come in as active partners to cocreate value to this health ecosystem.[72]

SUMMARY

Reflecting on the evidence presented and our Singapore pediatric health experiences, it is necessary to move away from the traditional hospital-centric model of health care and instead take a life-course approach and use a life-centric model for pediatrics. Population health in pediatrics should be the overarching platform in pediatrics of the twenty-first century: clinicians should not just cure diseases but should improve overall child health. Health care efforts should complement and potentially enhance public health efforts, involving the various stakeholders, similar to the example of a multilevel approach to childhood obesity. Clinicians need to move upstream and address the health and not just the health care issues of children, and adopt proactive instead of reactive approaches as health care providers in pediatrics.

Technology and telehealth, if properly positioned, will improve the delivery of health to the population in a dynamic and responsive manner and can transform health delivery from the current largely reactive mode to a proactive one, especially when it comes to

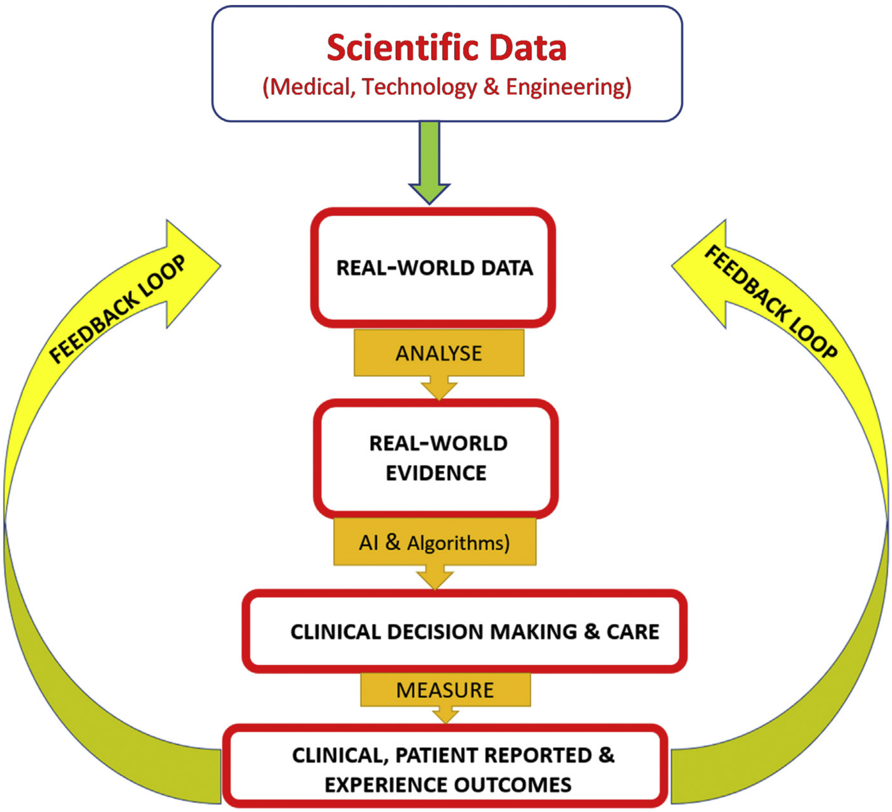

Fig. 7. A continuous learning health ecosystem.

promoting and improving health and not just managing diseases. Telehealth through social media cyberspace and IoT can bridge and provide solutions and interfaces between the current health and health care space and the community health space (Fig. 6).

Technology enables clinicians to capture big data and RWD in a continuous manner. AI and predictive analytics can help to make sense of RWD. Medical care can furthermore be personalized and calibrated to the specific and individual needs and requirements of specific patient sets and individuals. It enables clinicians to estimate the effects of targeted interventions on individuals and groups in diverse patient populations and translate these findings into impactful strategies to improve the overall health of children in the twenty-first century.

Clinicians can analyze and respond more promptly to various health and health care issues in pediatrics. Health care providers play an important role in providing anticipatory guidance, advocating for the evaluation of health care technologies, and creating an evidence-based platform for their communities. Technology calls for the collaboration of the various stakeholders to provide more integrated solutions, enabling clinicians to translate population science into population management. AI in pediatric, can enable a truly learning health ecosystem to be developed where RWD is continually leveraged to generate RWE to improve and enrich overall child health in the community (Fig. 7).

DISCLOSURE

The authors have nothing to disclose.

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