Chapter 2
Value-Driven Digital Transformation in Health and Medical Care

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2.1 Evolution of Patient-Centric Medical Care

Since the beginning of modern medicine, medical care has been practiced with a strong focus on the patients needs beyond re-stating the patient's health. We can find in Hippocrates oath the origin for both patient safety stating the *nonmaleficence* principle and patient privacy. Therefore, we can state that medical care has been patient centric from the very beginning.

The development of public health between late 1700s and beginning of 1900s [44] first and the rising of Evidence-based medicine (EBM) [19] later where attempts to provide a standard of care of the highest quality to all. The remarked focus on population, seemed like medical care had shifted temporarily the focus away from the patient as individual. On the contrary, public health and EBM were actually incorporating more needs of the patient into the care process, needs of the patient not limited to the individual but as part of a society.

As response to such apparent focus shift at the end of the twentieth century, a renewed person-centric effort spread through care practitioners and medical care associations aiming to refocus care back into the patient [43] incorporating more patient needs beyond the medical interventions it-self, including patient values and

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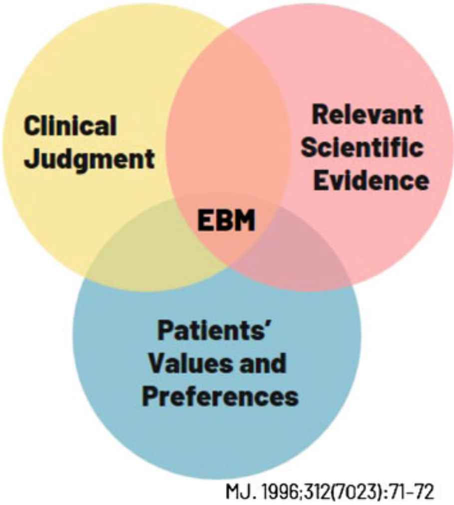

Fig. 2.1 EBM triade inspired on the original diagram in [38] from 1996

preferences. As a result, the EBM concept developed into the EBM triad, including patient values, needs and preferences as one of its fundamental pillars [38] (See Fig. 2.1).

2.1.1 *Holistic Approaches to Healthcare Improvement in a Patient-Centric Framework*

While the patient centric movement [8] continued growing through the first decade of this century, new trends about healthcare delivery raised to meet the incipient challenge caused by the global demographic pressure of a larger, older and sicker population: Healthcare sustainability.

Concepts like value based health care (VBHC) introduced by Porter and Teisberg [33] or the triple aim of healthcare [4] promoted by the Institute of Healthcare Improvement (IHI) acknowledge the complexity of the healthcare ecosystem and presented a more holistic approach to provide care taking into consideration all significant factors influencing the future sustainability of healthcare (See Fig. 2.2).

2.1.2 *VALUE Based HC Concept*

While Value-based healthcare is a framework with a holistic approach integrating several dimensions, the initial given definition of value [34] "as the health outcomes achieved per dollar spent" was relatively limited, reducing the whole concept to a mere cost-efficiency question. Fortunately for the sake of future sustainability the

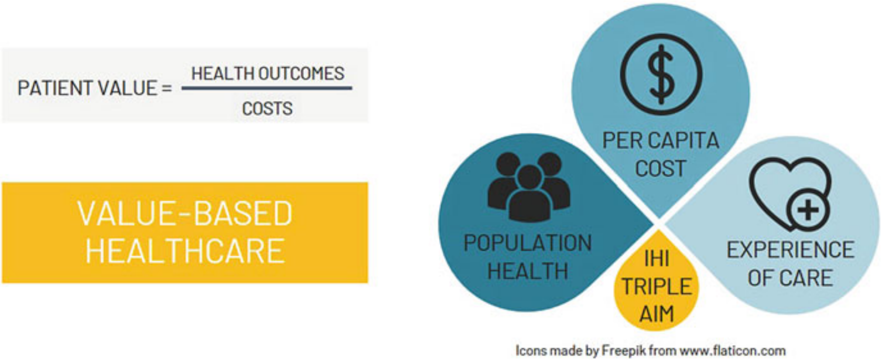

Fig. 2.2 Conceptual representation of Value-based Health care (left) and the triple aim of the Institute of Health Improvement

Table 2.1 Evolution of value definition in value-based health care. (**Source:** Modified from [10])

Narrow (price-based) utilization of *Value* [13, 16, 29, 31]	Value defined as the ehealth outcomes by dollar spent
	$$\textbf{Value} = \frac{\text{(Outcomes + Patient Experience)}}{\text{Cost(Direct + Indirect)of Care Intervention}}$$
	$$\textbf{Value} = \frac{\text{Healthcare that matters to the patient}}{\text{Cost along the entire cycle of care}}$$
Comprehensive (normative) utilisation of “value”[17]	Allocative value: equitable distribution of resources across all patient groups
	Technical value: achievement of best possible outcomes with available resources
	Personal value: appropriate care to achieve patients’ personal goals
	Societal value: contribution of healthcare to social participation and connectedness

definition of value has evolved in the last decade from a narrow, price-based, to a comprehensive, normative, definition, see Table 2.1 [10], not just preserving the wide holistic approach but making VBHC applicable to a wide range of healthcare systems.

2.1.3 *The Triple Aim of Healthcare with Attention for Health Care Professionals: The Quadruple AIM*

Simultaneously to the development of VBHC, the Institute of Healthcare Improvement proposed in 2007 a comprehensive framework to improve healthcare including population health in the triple aim [4] of healthcare. Conceptually very similar to VBHC, IHI's approach to health outcome was not limited to a specific disease and the care intervention provided. In the Triple aim, both the health outcome and the value for the patient were considered to a higher level: the whole population.

The three tenets building the Triple Aim are [4]:

- improving the individual experience of care,
- improving the health of populations and
- reducing the per capita costs of care for populations.

Probably, a wider framework that includes population health, i.e. incorporates the public health dimension with the patient centric approach and the financial aspect should be better useful to tackle the future sustainability challenge of healthcare.

Anyhow, it turned out that the triple aim was missing an essential component that is crucial for the other three tenets: The experience of the care team. As pointed out by Bodenheimer and Sinsky in 2014 [5] the triple aim cannot be achieved without including the wellbeing of the workforce. Any improvement achieved neglecting the experience of the health care staff will have a short-lasting effect, especially if it is achieved at their expenses. This way through the incorporation of the experience of the workforce, the triple aim evolved into the quadruple aim of healthcare [41] (See Fig. 2.3).

Fig. 2.3 Conceptual representation of the triple aim of the Institute of Health Improvement adding the perspective of the health care worker, known as the quadruple aim

2.2 Data-Driven Sustainable Healthcare Framework

2.2.1 International Consortium for Health Outcome Measures

The medical and healthcare community realized that the novel frameworks revolved around optimization concepts, targeting improvement, reducing cost and burden, increasing health outcome of intervention, and improving quality of life of patients. It was self-evident that the implementation of such holistic frameworks into practice required access to accurate information relevant to the different care processes. Not only such data should be condition specific but should be also standardized [12].

Health outcome measures have been collected and have been used for managing patients [36] for several decades. Accepting the claim by Porter in 2010 [30] that "Outcomes are the true measures of quality in health care" then measuring outcomes is indeed critical for assessing and maintaining the standard of quality of care provided to its prime.

Upon agreement that standardized health outcome measures were required to implement and maintain any healthcare improvement action [32] in any holistic manner, healthcare organizations collaborated and formed the International Consortium for Health Outcome Measures (ICHOM) in 2012. Since then, through a global collaboration effort ICHOM has developed more than 30 standardized sets of health outcomes measures with an evident patient-centric perspective.

ICHOM has identified and defined disease specific sets of clinical and Patient-Reported Outcomes Measures (PROMs), as well as Patient-Reported Experience Measures (PREMs) relevant for assessing value using outcomes that matter to patients and by doing so ICHOM has significantly contributed to spread the meaning of VALUE as the most comprehensive definition combining healthcare that matters to the patients with the cost along the entire cycle of care. This way unifying in a practical manner the conceptual frameworks proposed in VBHC and the multiple AIM of healthcare originally proposed by IHI.

2.2.2 Digital Health Transformation

Society as a whole and through specific branches has benefited from the application of advances in data storage, display technology, computing capacity and mobile data communications among others during more than a century, but specially in the two last decades. Despite that digital transformation is based on technological advances, it is not actually driven by technology but through the strategy of organizations aiming to meet certain needs or overcome specific challenges. The transformative power of novel technologies does not come from the enabling technologies but from the significance of the needs pulling for adopting given technological solutions, where disruptive innovation can multiply exponentially the value [22].

Table 2.2 Elements demanding a digital health transformation

Element	Constraints on Healthcare system		
	Patient	Cost	Quality
Population growth	Reduce access to care	Increase cost	Less time with patient
Increased patient demands	Demands better outcome	May lead to cost increase	Increase likelihood to perceive poor experience
Increased life expectancy	Increased likelihood to require care interventions	Increase cost	
Larger proportion of chronic patients	Patient required medical attention for life	Increase cost	Increase complexity of care delivery
Increased co-morbidities among chronic patient	Increased complexity of care	Increase cost per patient	
Care cost increase	Less budget available per patient		Less resources available
Inequity in care	Risk in drop in quality		Large variability

During the last 30 years a number of issues (see Table 2.2) have risen, demanding for changes in healthcare delivery of such magnitude that instead of changes it is actually a full transformation that is required, a transformation that can only be achieved through a paradigm shift (and thinking positively, the COVID-19 pandemic has pushed intensively towards such direction, forcing some of such expected changes).

As shown in Table 2.2, all changes, involve information: medical, clinical financial or patient-reported information and data. Basically, every single aspect of data is involved: collecting, storage, access, analysis, visualization, sharing, protecting etc. All the changes required to make future healthcare sustainable are data-related, consequently the seek transformation must be digital.

2.2.3 IT Infrastructure as Enabling Agent of Digital Transformation

The role of IT infrastructure and IT systems in health care has changed significantly in last decades. From originally heavily devoted to host the electronic patient record, basically just collecting the minimum necessary patient data and providing clinicians with limited access to patient data. IT systems at hospitals evolved to computer networks interconnecting the hospital databases, ensuring access to health-related data across the hospital and enabling information services to benefit all levels of the health care system [14].

Nowadays, IT systems at hospitals should focus mainly on data management, including data collection, data sharing, data presentation, preserving security and privacy while providing the data infrastructure required to leverage data analytics for both managerial, clinical and medical purposes. It is precisely the availability of high quality, relevant and shareable data, one of the factors digital healthcare transformation and consequently IT systems have become the core of the ongoing paradigm shift in healthcare.

2.2.4 Artificial Intelligence Widely Available for Contributing to the Transformation

Another enabling factor catalyzing digital transformation is Artificial Intelligence (AI). For over 40 years AI has been applied into medicine through the so-called Computer-Aided medical Diagnostics [1, 28] or Expert Systems [26, 40], but it has been during the last 10 years that AI has been incorporated into any future healthcare strategy. Such development has not been driven by only the strong pull of the market in need to meet increasing demands in number, expectations and complexity, but also by two very important facts:

- **Overwhelming number of success cases of AI analytics outside healthcare.** For over 40 years, enterprises have benefited from all sort of rule-based decision support [39] systems first, statistical descriptive analytics later and machine learning-based prediction analytics last. AI applications have showed their benefits through society from extremely application specific e.g. Identification of flicker disturbances in power quality [2], quality improvement in product manufacturing [23] to generic-daily life situations e.g. smartphone key typing [3], faceID unlocking tablets [6], best traffic route provided by google maps. Therefore, it is very well proven what AI-boosted analytics can do in basically any data-driven scenario.
- **The Birth of Big data.** The rapid expanding of big data through all branches of science, engineering [47] and business [25] fuelled by the emergence of the data scientist [11, 46] and the quick development of platforms for data management and cloud computing [20] like Hadoop prepared the runaway for AI predictive analytics to take off.

Through the years several different definitions have been given to AI, currently the official definition given by the EU parliament is the following “AI is the capability of a computer program to perform tasks or reasoning processes that we usually associate with intelligence in a human being.” In the right conditions, that is with accurate and trustable data available, AI solutions can have a significant impact in several areas of healthcare [21], see Table 2.3. AI enabling (1) improvement of

Table 2.3 Mapping AI potential impact areas with current constraint dimensions in Healthcare

Healthcare area	Cost	Quality	Patient
Self-care, prevention and wellness	x	x	x
Triage and diagnosis		x	
Diagnostics	x	x	
Chronic care management	x	x	x
Care delivery		x	
Clinical decision support		x	x

population-health management, (2) improvement of operations and (3) strengthening innovation would most likely will contribute to the revolution required to ensure future sustainability of the healthcare systems.

When mapping these potential areas where AI can make a difference with the constraints in healthcare imposed by the elements demanding a digital health transformation listed in Table 2.2, it is possible to identify a large overlap that indicates the true transformative power of AI in Healthcare.

2.3 Challenges and Adoption Barriers to Digital Healthcare Transformation

Despite the strong pull from the healthcare systems with needs specifically demanding solutions with the transformative power of digital technologies, there are all sort of implementation challenges, organizational hurdles and acceptance barriers stopping to fully embrace digital healthcare transformation just yet.

Many of those challenges and hurdles [24] are generally related to incorporating digital technologies and implementation novel data management approaches within hospital operation and clinical practice but others are specifically related to aspects of AI.

2.3.1 Data Management Clash

Availability of all sort of data, patient, operational, financial, medical, is one of the catalyzers behind digital transformation, but patient privacy from one side and data interoperability [18, 27] issues from another are slowing down adoption of digital healthcare.

Legislation to enforce patient privacy should be in place, and in Europe, the GDPR has precisely defined it to preserve the privacy of everyone in the current information era. Unfortunately for Big Data Analytics in healthcare, GDPR is limiting heavily potential applications at the moment due to uncertainties from legal stand points of what can be done or not with certain data and how and in which way it should be interpreted to preserve the legal framework defined by GDPR [9]. This caution has resorted in many healthcare organizations through Europe to complete standstill, awaiting for other first adopters to present viable solutions, or specific guidelines from European or national authorities about how AI and big data analytics should be implemented under the umbrella of GDPR.

The true potential of big data AI-driven analytics requires that all sort of data is collected, stored, computed and visualized in completely different IT systems, that implies that data is shareable through the IT systems. Unfortunately, that is not the case in most of practical scenarios. Despite important initiatives to define interoperability frameworks for data sharing, currently, old legacy systems remain being active and used among hospitals all over the world slowing down the path to the digital healthcare transformation journey.

2.3.2 Organizational Self-awareness for Digital Adoption Readiness

The journey towards digital health transformation requires to interconnect many different dimensions within a care organization and requires certain level of readiness across the whole organization to implement any data analytics strategy, otherwise the implementation will fail and the potential benefits will not be achieved. The depth of such interrelation required to successfully implement any given data analytics solution is commonly underestimated, between the manual collection of a given parameter during daily routine to the availability of such value in a database of a hospital information system may pass days even weeks. Moreover, just because the parameters are digitalized, further data manipulation might be required due to incompatibility issues and lack of interoperability.

2.3.3 Inherent Risks of AI

Data analytics boosted by AI is certainly very useful but even when used to analyze what happens it is not infallible and is subjected to external factors, human error often. When AI is boosting predictive data analytics, the source of error might not be only external but inherent to the core fundamentals of AI.

One of the fundamental pillars of AI is a strong statistical core, the more solid the statistics available for an application the more accurate the analysis will be done and the more certain the predictions. It happens that when the number of cases are low the supporting statistics will be poor and the produced prediction will not be reliable. Inconveniently, in medical care when a practitioner is unsure and requires support this is often not with common everyday cases, where AI-support potentially will perform at its best, but with odd and complex cases, for which AI predictions will fail most often. Such kind of performance issue when AI is needed the most, creates a bad reputation and produces mistrust among practitioners that will impact their acceptance.

Limited traceability is also a common and significant downfall when dealing with machine learning based algorithms. In medical care patient safety and quality of care in general are critical factors driving clinical operations. Therefore, when there is a failure, sources must be identified, and measures should be taken to prevent the same failure to occur again. While the learning capacity of AI systems will potentially and eventually deal after several failures, preventing the miss-judgement, the opacity of [35] black-box model at the core of the most of AI algorithms will make it impossible to trace back the stage within the algorithm that failed and led to a wrong prediction. Nowadays in normal circumstance in clinical practice it is not acceptable to work with a tool that if it fails, the source for the failure cannot be located.

The inherent probability of an error in certain circumstances, and the lack of the true understanding of the underlying process at the core of the AI process, will impact heavily the acceptance of most clinicians to adopt the use of these tools into clinical practice.

Even in organizations with high data analytics maturity and strong user pull to incorporate already-proven innovative technologies, and even when considering the current landscape of AI solutions provided by trust-worthy vendors of established reputation, the task of selecting the most appropriate technological solution is tedious and complex, and requires a careful planning incorporating a holistic approach.

2.3.4 Actions to Reduce Challenges, Hurdles and Barriers

The shadow casted by the relatively novelty of the GDPR over healthcare organization requires certain guidelines with clear examples from the responsible authorities or the development of best practice guidelines to enlighten up the journey.

A well-thought strategy to implement digital health transformation accounting for all aspects intertwined with the future implementation steps required to take would definitely facilitate the digitalization journey. Such a strategy should be designed according to the maturity level of the organization for adopting data analytics and the implementation should be paced accordingly to the progression of the maturity level for adopting data analytics of the healthcare organization.

For nearly a decade ago, HIMSS, the Healthcare Information and Management Systems Society, developed the adoption model for analytics maturity (AMAM) and has been using it to support healthcare organizations to evaluate and advance their own analytics capabilities. HIMSS in a new effort to support healthcare organizations to eliminate organizational challenges and technology readiness barriers has just launched the HIMSS Digital Health Framework [42] and the Digital Health Indicator.

A framework based on the seven maturity levels developed by HIMSS and an indicator to measure progress towards a digital health ecosystem by measuring both operational features of digital health systems, as well as transformation of digital care delivery.

The trust of clinicians and medical managers is critical to increase the acceptance of AI solutions within healthcare. Education actions targeted to improve the understanding of the black-box engine driving the AI algorithms would increase the technology readiness of users and decision makers but the true impact on improving understandability among clinical stakeholders would come from using understandable AI methods with an inclusive methodology engaging the clinician in the whole AI modelling process.

Under the umbrella of Artificial Intelligence and information theory, Process Mining [45] is a research discipline that uses existing information to create human-understandable views that support healthcare stakeholders in enhancing their insight in the clinical process. One of the distinct features of process mining is that it focuses on the analysis of logs of activities from process creating visual models. The direct visualization of the modeling output and direct connection of the model elements with the source provides the method with a transparency that allows to identify causality and enhance traceability. Such transparency is the opposite of a black box model and it is an incentive for users in the health care field, demanding to be able to inspect the inside of analytical and predictive core.

A novel interactive process mining methodology [15] has been developed that specifically requires the engagement of the clinicians in the extraction of the operational model. Such engagement provides the clinician with insights about the internal functioning of the analysis phase that preserve their trust, wondering the reasons and engaging them in the continuous improvement loop, following a question-based methodology [37].

Another initial advantage intrinsic to process mining analysis methods is that the object of study are processes from events logs not patient data per se, therefore reducing constraints imposed by preserving privacy.

Availability of evidence is critical to reach an acceptance across the health and medical care community, therefore a well-documented catalogue of success cases of improving healthcare through assessing value for patients using digital health solutions is required.

Giving the need for healthcare improvement with a holistic perspective and the target pursued by process mining, improvement of output based on the key performance processes, seems like a match difficult to overlook.

2.4 Summary

Medical care has been patient centered from the origin and has evolved closely along the evolution of patient needs from the patient as individual to the patient as population, pursuing to provide the medical care of the highest quality standard.

The holistic unification of patient individual health and patient population approaches through health and patient outcomes as predicted by Cairns back in 1996 [7] and has been catalysed first by the availability of information technologies and then the rising and development of VBHC.

Considering value in VBHC as achieving the best outcomes from the perspective of the patient versus executing the care process needed to achieve these outcomes in the most optimal way. It is of paramount importance to identify and understand the processes to be improved in order to be able to improve the outcomes.

Digital health tools enable deployment of information services and data analysis technologies like process mining precisely adequate for discovery, analysis and optimizing of the operational models underlying the actual care processes.

Despite that the undergoing transformational change is pulled by global needs and driven by information technologies, data availability and data science, the journey ahead for digital health transformation is full of all sort of barriers: regulatory, clinical adoption, medical trust, and patient acceptance.

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