

Health Informatics Workforce in the Digital Health Ecosystem

Rebecca MEEHAN^{a,1}

^a*School of Information, Kent State University, Kent, OH, USA*

Abstract. Workforce development needs to align with the healthcare data ecosystem emerging from digital transformation in healthcare. Careers for health informaticists are emerging as translational agents between clinicians and data scientists. Digital tools and mechanisms in healthcare, through electronic health records (EHR), devices, capabilities including artificial intelligence (AI), machine learning (ML), interoperability and health information exchange (HIE) allow clinicians and stakeholders to capture, store, access and use health data and information in ways unseen in years past, creating a new digital health ecosystem. This transformation is evolving both technologies and the strategies to influence health outcomes. Careers in health informatics are now part of this data ecosystem, and it is important to examine the current status and its implications for job seekers and for workforce development.

Keywords. Workforce development, digital transformation, health informatics.

1. Introduction

Digital transformation is reframing human experience in the 21st century. The development and accelerated advancement of digital technology has prompted change across virtually all aspects of human experience [1]. This includes healthcare. There is a global trend in utilizing digital health tools to create opportunities, improving healthcare through patient-centered, health information technology (health IT) [2]. Since the global proliferation and the widespread adoption of EHRs in the United States after 2010 [3] there is exponential growth in the volume of health data collected from patient records and tests. In this evolution, workforce development is critical.

Health informaticists are finding new and growing career opportunities to use data and information to improve health and healthcare, specifically aligned with data science. Health informaticists have an interdisciplinary approach with work that sits at the intersection of health, information technology and social and behavioral science [4]. In parallel, data scientists develop insights from leveraging structured and unstructured data, using scientific methods, data mining techniques, machine-learning algorithms, and big data [5]. As the two fields of health informatics and data science work together to improve health, there are opportunities for improvement and efficiency. Health informaticists often work as translators between data scientists and technology specialists and the people in healthcare (clinicians and patients).

Advancements in digital health tools create new opportunities in clinical decision support, engagement of patients, and improved quality of care. These advancements require new considerations of ethics in health information and use of health technologies [6]. Dr. John Halamka describes Mayo Clinic's digital platform as being built to allow for predictive analytics, and to turn healthcare data into wisdom (Bruce, 2022). He

¹ Corresponding Author: Rebecca Meehan, email: Rmeehan3@kent.edu.

continues that the platform was built to allow for less invasive, more timely, less costly care and allow for better wellness [7].

As a professional field in health informatics, we can prepare students with knowledge, skills, and abilities to support the data ecosystem lifecycle as it aligns to the foundational domains of the profession (AMIA, HIMSS, etc.). Part of this process should entail introduction and interprofessional opportunities in data science concepts, technologies, and projects. In a like manner, preparation for data scientists in healthcare should introduce concepts, practices, and projects in the health informatics domain. In this way, health informaticists align with data science processes to bridge the gap between innovation and big data with clinicians and patients. Informaticists work to understand the requirements of what clinicians and patients need, and then can relay this back to data scientists and technologists to ensure the right problem is being solved. This continuous feedback and communication pattern continues with health informaticists and begins to support new jobs for these roles.

2. Methods

The data ecosystem proposed in this paper (Figure 1) was derived from interviews with data science leaders in health care. Still, the data ecosystem proposed in this paper (Figure 1) aligns closely with a data science lifecycle [8], including business understanding, data understanding, data preparation, model planning, model building, evaluation, deployment, and review and monitoring. The data ecosystem creates opportunities for workforce development and careers along each part of the pathway. A central component to any health informatics job is working with health data and information. Whether in health care or any other industry, most data related jobs can be categorized into a data ecosystem (see Figure 1). Health informatics roles generally incorporate strategies and tasks to support them around how health data is acquired, organized, normalized, secured, analyzed, archived, and shared. While digital health tools will continue to evolve, the process around data and information in health care will likely remain consistent. In healthcare, these data ecosystem jobs continue to change names, and are guided by health care specific regulations, laws and data governance principles.

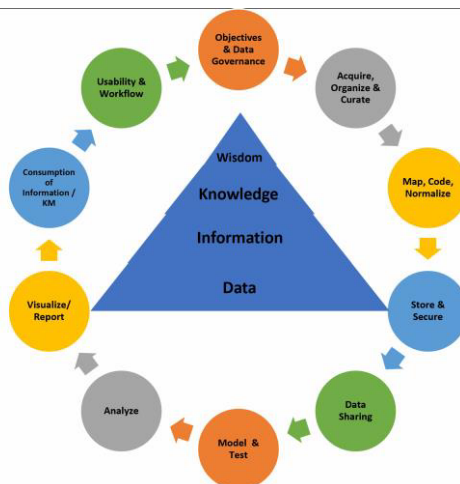


Figure 1. Data ecosystem for health informatics

The data ecosystem contains the processes for how data is transformed and used to inform stakeholders, creating opportunities to move from data, to information, to create knowledge and wisdom for stakeholders. Not only is it important to understand how we derive knowledge from health data, but it also gives us insight to the roles and responsibilities associated in each stage, with many jobs directly related to health informatics. Workforce development programs in this area need to understand how each of these roles works as part of a larger data system. Figure 1 categories are described below.

-Objectives and Data Governance: This area focuses on why data is being collected, and what the rules are around how data will be collected, stored, accessed, and used.

-Acquire, Organize and Curate: Based on the objectives for why data is collected, and the rules of accessing and using the data through data governance principles, data is acquired or downloaded from one or more sources. It then needs to be evaluated and organized and will be influenced by a data curation process. Data curation involves managing data throughout its lifecycle.

-Map, Code and Normalize: Managing data and preparing it to be shared and analyzed entails a normalization process, coding and mapping for consistency in the description of data and its associated codes. For example, if EHR data is coming in from different sources and systems, it may be coded differently for the same health element. Similarly, mapping vocabularies (e.g. SNOMED) from one data set to another is an important step in normalizing the data. These processes not only prepare data for sharing and use, but it also enables it to be used in data mining, artificial intelligence, and machine learning processes.

-Store and Secure: Storing and securing the data allows it to be accessed and used for a duration of time, without having the data compromised by hacking and loss, and to ensure that it is available for routine processes. Cybersecurity strategies are integrated here.

-Share: As data is collected, organized, mapped, stored, and secured, it is essential to have the capability to share data. To facilitate interoperability, data needs to be in a compatible format to share, leveraging industry standards (e.g., HL7 FHIR, etc.).

-Data Modeling: The first step in the process in database design is data modeling [9]. The aim of data modelling is to describe a) the entities and data contained in the database; b) the relationships between data; and c) the constraints on data (e.g., number of digits).

-Analyze: As data moves through this lifecycle, it can be analyzed based on the needs of the organization. Data sets can be any size, ranging from small and manageable on site to other health care data sets incorporating millions of patient visits, resulting in terabytes of data. This needs to be considered for proper capacity for storage and analytic power.

-Visualize and Report: Many stakeholders will require a report for regulators, investors, or researchers. Data visualization techniques, including dashboards, can be very useful in helping the user to make sense of the data to inform decision making.

-Consumption of Information: Stakeholders will then be able to consume and use information for clinical decision support, reporting or other reviews helping to move forward to knowledge and wisdom.

-Usability and workflow: This stage represents reflection on the information and knowledge process. It engages end users for feedback on workflow, or how usable the data and interface may be.

3. Results

Throughout the data ecosystem, there are stakeholders who are involved, as consumers, monitors or contributors to that given area. As such stakeholders can include the 1) person responsible for completing the job in that area (worker), 2) providers, patients, and caregivers, who need to be informed about that area, and 3) the manager who must oversee that area and communicate with others across the data ecosystem. Workforce development can anchor training strategies in the data ecosystem inclusive of the many disparate health information partner organizations.

3.1. Similarity to other Data Science Process Models

There is overlap and similarity between the proposed health care data ecosystem and other data science workflow models [8]. For example, a typical data science workflow diagram with the following stages in an ongoing cycle: 1) data science problem framework, 2) data acquisition, 3) data exploration, 4) data modeling, 5) communicating and visualizing results, 6) reflection or inference phase [10]. Commonly used data science process models include the a) Harvard, b) CRISP-DM, c) OSEMN, and d) AWS, among others. All of these models incorporate some components of the following stages: problem framework, data acquisition and cleaning, data exploration and modeling, evaluation, communication, and deployment and performance modeling [10].

4. Discussion

Workforce development for health informaticians needs to focus on the practice of health informatics, that is more about what people are contributing, and less about the technology or data [6]. Hersh (2006) forecasted the importance of the health informatics workforce in the digital health ecosystem when he discussed the necessity of the “professional workforce that will deploy systems outside of academic research setting so their benefits may more widely accrue” [11]. These health informatics roles serve as a translator for technological advancement with application to clinical outcomes, facilitating the full value of digital health and data science capabilities [6].

Informing workforce development programs will involve helping job seekers to be aware of why data in certain areas need to be collected, what the best data processes are, how to manage and share insights from healthcare data from current systems, as well as being prepared for future changes. Workforce development will require capacity building associated with data use and decision making, time demands of engagement and changes in the doctor-patient relationship [12]. These advancements require new considerations of ethics in health information and use of health technologies [6]. Data scientists are focused on deriving value from data [8]. This overlaps with the role of health informaticians, who seek to improve healthcare using data and information. How can we best prepare digital health specialists to contribute to improving outcomes?

The health care data ecosystem (Figure 1) shows the processes for how data is transformed and used to inform stakeholders, creating opportunities to move from data to information, to create knowledge and wisdom for stakeholders. Not only is it important to understand how we derive knowledge from health data, but it also gives us insight to the roles and responsibilities associated in each stage, with many jobs directly related to health informatics. Workforce development efforts need to align to these phases of the data ecosystem to be most prepared for future opportunities for health informatics professionals. Health informaticists play an important part in digital transformation, as they are working in every area of the data ecosystem. Because health informaticists can serve as a bridge between clinical specialists and data scientists, as

translational informaticists, they help to keep this process of moving from data to wisdom moving forward.

5. Conclusions

Workforce development programs for health informaticists need to consider the evolving landscape of careers aligned with data science lifecycle. As healthcare faces the challenge of moving from “coding to bedside” we need data scientists who keep the end user and related stakeholders in mind when developing new techniques and tools. They need to be aware of the practice of health informaticists who help to bridge the knowledge gap between and among clinicians, patients, administrators, regulators, and data scientists to improve health care using data and information.

References

- [1] Abernethy A, Adams L, Barrett M, Bechtel C, Brennan P, Butte A, Faulkner J, Fontaine E, Friedhoff S, Halamka J, Howell M, Johnson K, Long P, McGraw D, Miller R, Lee P, Perlin J, Rucker D, Sandy L, Savage L, Stump L, Tang P, Topol E, Tuckson R, Valdes K. The Promise of Digital Health: Then, Now, and the Future. *NAM Perspect.* 2022 Jun;2022:10.31478/202206e, doi: 10.31478/202206e.
- [2] World Health Organization (WHO). Global strategy on digital health 2020-2025. Geneva: World Health Organization; 2021. Licence: CC BY-NC-SA 3.0 IGO.
- [3] Office of the National Coordinator for Health Information Technology. Health Information Technology for Economic and Clinical Health Act (HITECH). Sec. 3001. February 2009.
- [4] American Medical Informatics Association (AMIA). What is Informatics? 2022. <https://amia.org/about-amia/why-informatics/informatics-research-and-practice>.
- [5] Subrahmanya SVG, Shetty DK, Patil V, Hameed BMZ, Paul R, Smriti K, Naik N, Somani BK. The role of data science in healthcare advancements: applications, benefits, and future prospects. *Ir J Med Sci.* 2022 Aug;191(4):1473-1483, doi: 10.1007/s11845-021-02730-z.
- [6] Scott P, Dunscombe R, Evans D, Mukherjee M, Wyatt J. Learning health systems need to bridge the ‘two cultures’ of clinical informatics and data science. *BMJ Health Care Inform.* 2018;25, doi: 10.14236/jhi.v25i2.1062.
- [7] Bruce G. Mayo Clinic Platform leader Dr. John Halamka is turning 'healthcare data into wisdom'. July 14, 2022. <https://www.beckershospitalreview.com/innovation/mayo-clinic-platform-leader-john-halamka-md-turning-healthcare-data-into-wisdom.html>.
- [8] Song IY, Zhu Y. Big data and data science: what should we teach?. *Expert Systems.* 2016 Aug;33(4):364-73.
- [9] Watt A. Data Modelling. In: Watt, A. and N. Eng. (2014). *Database Design – 2nd Edition*. Victoria, B.C. <https://opentextbc.ca/dbdesign01/chapter/chapter-5-data-modelling/>.
- [10] Kishore A. A Layman’s Guide to Data Science Workflow. 2023; <https://www.knowledgehut.com/blog/data-science/data-science-workflow>
- [11] Hersh W. Who are the informaticians? What we know and should know. *J Am Med Inform Assoc.* 2006 Mar-Apr;13(2):166-70. doi: 10.1197/jamia.M1912.
- [12] Marjanovic S, Ghiga I, Miaoging Y, Knack A. Understanding value in health data ecosystems. A review of current evidence and ways forward. In: *Rand Health Q.* 2018 Jan;7(2):3.