AI Solutions for Inter-organisational Care: A Case Based Analysis

Jöran Lindeberg[1(✉)], Martin Henkel[1], Erik Perjons[1], Paul Johannesson[1], and Katarina Fast Lappalainen[2]

[1] Department of Computer and Systems Sciences, Stockholm University, Stockholm, Sweden
{joran,martinh,perjons,pajo}@dsv.su.se
[2] Department of Law, Stockholm University, Stockholm, Sweden
katarina.fast@juridicum.su.se

Abstract. Health care is a complex domain containing large amounts of data, including clinical and administrative data. Furthermore, the domain includes advanced decision-making utilising the collected data. Various IT systems based on AI technologies, such as machine learning, have been promoted as a way to improve both the quality and efficiency of health care. So far, the focus has been on supporting quite narrow and data-intensive activities carried out by a single actor, such as interpreting X-ray images and performing triage. However, providing health care for a single patient can involve a comprehensive process with numerous actors, ranging from home care and primary care to specialist care. In this paper, we examine how existing AI solutions can support a complex care process involving several collaborating actors. We base the examination on a health care case from Swedish elderly care. The case is used to identify multiple problem areas, which are then compared to existing AI solutions.

Keywords: AI · Inter-organisational Collaboration · Healthcare · Health Informatics · Elderly Care

1 Introduction

As recognized by Davenport & Kalakota [4], Artificial Intelligence (AI) and other data-driven solutions have great potential for improving health care. Furthermore, AI has already been used successfully to support single tasks in health care, for example in image processing. However, there are many other parts in healthcare that has the potential to be transformed by AI. From a system theory perspective, many healthcare systems can be characterised as Complex Adaptive Systems (CAS) [18], where the same patient often interacts with a plethora of more or less independent actors, public as well as private, which are governed by different governmental entities. Thus, taken as a whole, the health care of a patient becomes a complex inter-organisational process rather than a number of single isolated tasks.

A. Rocha et al. (Eds.): WorldCIST 2023, LNNS 799, pp. 538–549, 2024.
https://doi.org/10.1007/978-3-031-45642-8_52

If AI could be leveraged to improve the collaboration between healthcare actors that work in complex inter-organisational processes, it has the potential for strong outcomes at the system level. However, there is a lack of implementation of such system-supporting solutions in real healthcare processes. The aim of this paper is to examine how existing AI solutions could support complex care processes. This research is part of an ongoing case study examining how Region Stockholm and Stockholm Municipality care can improve collaboration in the health care area. Improved collaboration is important for all residents—but crucial for elderly people that are in more frequent need of special care (provided by the region) and home care (provided by the municipality). Tentative results from the case study focusing on issues with IT systems and hindering legislation have already been published in a report in Swedish [6]. Parts of the findings were presented as an archetype patient, "Alex", representing the health care contacts of an elderly person. The case was designed to illustrate how the different actors collaborate, and to what extent various IT systems support this process. In this paper, we are using the case of Alex to highlight the many problems we encountered and map them to possible AI solutions.

This paper is structured as follows. Section 2 presents AI and its use in health care, Sect. 3 explains the method employed in the case study, Sect. 4 describes the case study and the illustrative Alex case example, Sect. 5 presents the identified problems and AI solutions, Sect. 6 and Sect. 7 concludes the paper.

2 Related Research

There have been ambitious efforts to give general views of AI in health care. One systematic study [5] from 2019 of AI use in Swedish health care found that there has been much research but considerably less implementation. Furthermore, Mehta el al. [12] conducted a systematic mapping study of 2,421 research articles from between 2013 and 2019, presenting them according to a number of dimensions. Compared to these efforts, we have a different purpose: rather than trying to give a complete overview of all solutions, we particularly focus on solutions that help solve problems in real-world inter-organisational care process. Moreover, we concentrate on solutions that have already been incorporated into clinical practice, which limits the scope considerably. It relates primarily to what according to a classification scheme by Mehta el al. [12] is called "healthcare operations", one of 37 sub-categories.

Generally, AI is "the capability of a machine to imitate intelligent human behavior" [13]. Several different categories, and sub-categories, of AI has been implemented in health care. Drawing mostly from Davenport & Kalakota [4] and [10] we utilise the following high-level categories of AI in health care:

– *Supervised machine learning* uses labeled data as training data to be able to correctly categorize new, unlabeled data.
– *Unsupervised machine learning* finds hidden patterns in unlabeled data, e.g. finding clusters of data according to common characteristics.

- *Rule-based* AI utilizes decision rules based on human domain knowledge. It delivers predictable decisions based on pre-defined rules.
- *Robotic Process Automation* (RPA) is a type of AI that often acts as a human user in a system. It can be both rule based or learn from how a human performs certain simple tasks in e.g. a software interface.

Another way to classify health care AI is according to its data sources [10]. These include, e.g., patient records, communications (e.g. text messages), and surveys (e.g. questionnaires to patients).

The implementation of AI in clinical practice has been limited. According to Panch et al. [15], there are two primary reasons. First, healthcare systems are complex and fragmented, and will not easily change as a result of new technology. Second, most healthcare organisations lack the capacity to collect the necessary training data of sufficient quality while also respecting ethical principles and legal constraints. Thereby, health care AI still has a stronger presence in research than in practice. Existing AI solutions can be categorized according to their implementation level. Many are just concepts, others exist as prototypes, some have also been tested, or actually used in regular care practice.

3 Method

To study the existing care processes and collaborations, a case study was set up, and personnel at both the region and municipality was interviewed. In addition to this, information was also gathered from legislation (that sets rules for information exchange between parties) and documentation of the IT systems that were used. The interviews led to the identification of *problem areas* and also the documentation of an *illustrative example case* that was used to illustrate how the archetypical patient Alex is handled by the municipality and region and the problems encountered.

A total of 8 people were interviewed, out of these 3 were also involved in follow-up interviews to extend the data. Furthermore, 9 IT systems were examined. The problem areas were then synthesised into a thematic map using the Kumu.io tool. An overview of the method can be seen in Fig. 1.

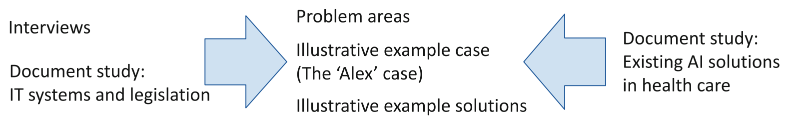

Fig. 1. Overview of the method

The existing AI-based solutions were found by a mapping review [8] of literature from 2015 and onward, including the two significant structured literature surveys [5,12] mentioned in Sect. 2.

Our main interest was in solutions already implemented in clinical practice, and such solutions may or may not have been covered by academic literature. Therefore, our search strategy included both articles from scholars and non-academic sources, such as reports from public organisations. Since the identified problem areas concern inter-organisational collaboration in healthcare, solutions without relevance for such aspects were excluded, e.g. for medical treatments.

To structure the solutions, they were first categorized according to three dimensions: AI type, data source type, and implementation level. Then, the solutions were mapped to the problem areas—each problem area was associated with those AI-based solutions that could help address the problems in that area.

4 The Stockholm Health Care Case

The healthcare in Stockholm is structured into two main responsible entities—Region Stockholm and Stockholm Municipality. While the region is responsible for primary care and special care, the municipality is responsible for home care and nursing homes. To illustrate how the actors get involved in the care we created the archetypical case of Alex based on the interviews (see Fig. 2).

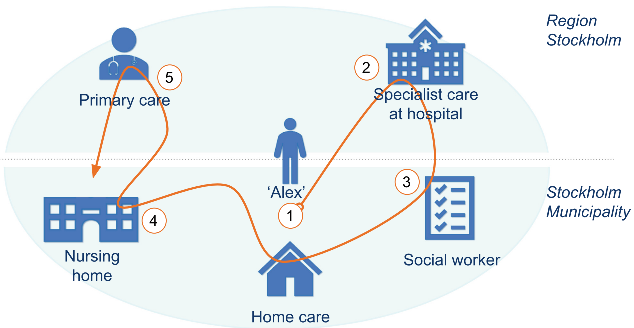

Fig. 2. Overview of the Alex case

The case starts with Alex living at home, receiving home care a few times per week (1). When Alex falls and gets injured, Alex needs to be transferred and treated at a hospital (2). When recovering, a municipality social worker needs to get notified and create a new home care plan (3). However, as there are complications Alex is transferred to a nursing home (4), and regularly needs to visit the primary care (5) for follow-ups.

While the case seems sequential and straightforward, there are a number of issues that makes the case more complex. To start with, the region and municipality are governed by different legislation, sometimes hindering information exchange. Furthermore, all actors use different IT systems that are only partially integrated. Therefore communication to some extent still relies on phone calls and fax.

5 Identified Problems and Solutions

This section presents the identified problems in the case study, and describes the found applicable AI solutions. Out of the 17 solutions, only five had been implemented in regular care.

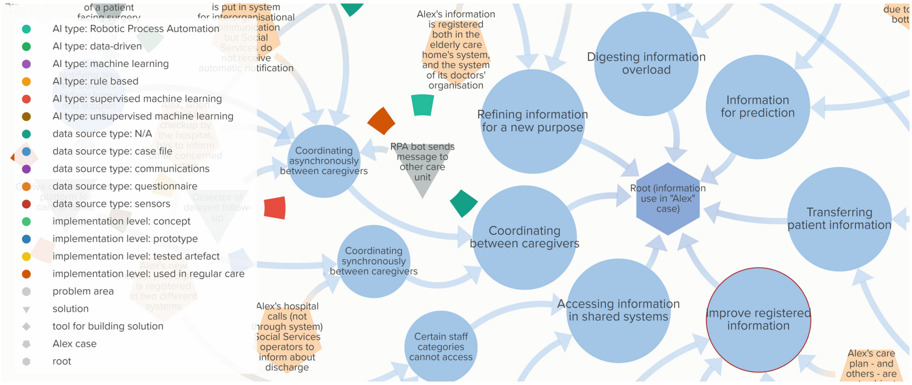

Fig. 3. Central view of the resulting Kumu.io map. Circles represent problem areas, pentagons are issues from the Alex case, and triangles represent solutions. The complete map is available at https://kumu.io/joran/stockholm-health-care-case-ai-solutions-map

5.1 Coordinating Between Caregivers: Asynchronously

When Alex is discharged from the hospital, it informs the municipality's elderly care unit through a common system developed for the particular purpose of exchanging information between caregivers. This is stipulated in specific provisions making the exchange of information possible in this area. This is important as the different organizations involved are generally bound by strict requirements of confidentiality in regard to patients.[1]

However, the system in use cannot send a notification to the elderly care unit. Instead, a social worker has to access the system several times a day to check manually. Obviously, if the communication between caregivers fail, Alex runs an increased risk of being left without attention.

From the point of view of the elderly care unit, a possible solution to address the absence of notifications could be Robotic Process Automation (RPA). One example has been used at a Swedish hospital [20]. An RPA digital agent was instructed to constantly check new arrivals to the Emergency Rooms (ER) unit

[1] Act regulating the cooperation in relation to discharge from inpatient health care *(Lag (2017:612) om samverkan vid utskrivning från sluten hälso- och sjukvård)* and Ch. 25 § 11 Public Access to Information and Secrecy Act (2009:400).

against cases referred by the elderly care administration in another system. When a match was found, the digital agent made a note and also alerted the ER staff. Thereby, no cases were missed and the administrative burden of the nurses was reduced.

As mentioned, an RPA digital agent can operate much like any human user via the application user interfaces. Therefore it can be implemented without the complexity of actual system integration. A disadvantage is that the performed tasks are relatively simple. Moreover, there can also be legal problems related to having a digital agent access a system originally designed for human users only. This was indeed the case of the Swedish region above [20].

Regarding the mentioned risk of follow-up failure, there are also other AI solutions in progress. Murphy et al. [14] has tested a solution that applies machine learning on patients' case file records to identify people who have received worrying results from X-ray scans but have not received follow-up. A similar solution could be used in inter-organisational contexts if enough parts of the patient case files are shared among different caregivers.

Coordination between caregivers can also be accomplished indirectly. In Sweden the different regions share the health service "1177", which people access by either a browser or by making a phone call. The advice that may be given via the service include referrals to caregivers. Hence, even if the actual communication is between 1177 and the patient, the result is a coordination between caregivers. One way to improve this coordination is the use of chatbots, of which one example is Operationskollen [9].

5.2 Coordinating Between Caregivers: Synchronously

In the case study, a problem with asynchronous communication (such as via email) was identified: in some cases the care givers simply needed a speaking partner to solve pressing issues. Therefore a need for the used systems to support synchronous communication between caregivers was identified. Presently, this is primarily solved by phone, but it could preferably be integrated into the systems. One advantage would be increased efficiency, e.g. if users could identify in the system who is available for communication. Moreover, productivity tools produce data about a socio-technical system's operations that in turn can be used for machine learning of other solutions based on machine learning. Consequently, if synchronous communication were logged by the system, this would pave the way for future AI solutions.

Systems with integrated support for synchronous communication between caregivers exist already. For example, such a communication platform can provide communication channels in the form of both chat, voice and video, in order for patients, caregivers, and family members to have a dialogue about the current health status [3].

5.3 Improve Registered Information

In modern health care, a single patient can generate much documented information. In spite of this, important aspects are sometimes omitted. For example, the hospital may miss documenting Alex's ability to handle everyday activities, i.e. Alex's Activities of Daily Living (ADL) status. ADL is important for the municipality's elderly care social workers to determine what help Alex needs at home.

Regardless of whether a piece of information has been registered by a human user or a robot, technology can be used to ensure its quality. Schneider-Kamp [19] has developed different concepts and prototypes of supervised machine learning solutions to ensure quality information in the context of Danish care. The training data was based on client case files, complemented by data about the users. This approach would allow creating solutions capable of understanding which pieces of information that can be expected to be in a report given the type of report and the other information therein. Thus, if Alex's ADL status was missing, this could be flagged for the hospital staff.

5.4 Managing Information Overload

When Alex is discharged from the hospital, there is a risk that a large amount of heterogeneous data is provided by different professionals in the hospital. This may result in information overload for the social worker receiving the discharge information, which may not be relevant to the task at hand [19]. It can also be problematic from both a patient security and data protection perspective.

Schneider-Kamp has, as mentioned above, developed different concepts and prototypes of supervised machine learning solutions [19]. Also for this problem as solution was developed with training data based on client case files, complemented by data about the users. This strategy allows creating solutions capable of: (1) highlighting the most relevant parts of a text mass in a particular situation, (2) showing the latest changes, which tend to contain the most relevant information, or (3) sorting sections according to the estimated needs of a user.

5.5 Refining Information for a New Purpose

During Alex's care process, on several occasions, partially overlapping information will be registered at different places. For example, when Alex is about to be discharged from the hospital, its staff will need to spend time to find information that is already in the case file, and register it in the common system for the exchange of patient information between caregivers.

We found no specific solution to this problem in the scope of this study. On a general level, however, Natural Language Processing (NLP), which often builds on supervised learning, can be used to analyse unstructured clinical notes [4]. Exports or printouts from other systems, as in Alex's case, could also be processed. Another AI solution would be to use RPA to copy and paste data from certain sections of the clinical notes, if the information in the source system was structured enough. Either way, the results would have to be checked and corrected by a human.

In addition, legal issues might arise regarding purpose limitation, which means that personal data, such as health data cannot be reused for another purpose than the original purpose, unless it can be legitimized by, for example, the public interest or research purposes. Repurposing thus has to be compatible with such provisions.[2] Within the EU, recently introduced legislation, the Data Governance Act and the proposed European Health Data Space might expand the possibilities to re-use health data and other personal data.[3]

5.6 Transferring Patient Information

Another recurring problem in Alex' care process was difficulties in transferring patient information due to lacking interoperability. Note that we mean interoperability in more than the technical sense, and also include e.g. legal and policy issues [16]. For example, if Alex, when living at a nursing home, decides to change doctor, there is a risk that the patient case file would have to be transferred by fax and partly re-digitized.

Just like the problem of refining information for a new purpose, no specific solution was encountered for this problem. For want of increased interoperability, a possible work-around could again include NLP and RPA. If paper has been used as medium, scanning with Optical Character Recognition (OCR) can return it to its digital origin. Legal and organizational changes should also be considered, to make way for more flexible solutions.

5.7 Accessing Information in Shared Systems

Yet another recurring problem during Alex's care process, is when relevant information is available in a system that is to some extent shared, but there still are certain organisations or staff categories that do not have access rights. For example, nursing homes as well as the hospital's nutritionists and work therapists are for different reasons excluded from the mentioned inter-organisational exchange system.

We found no solutions to this problem that are in the scope of this study. It is rather a question of regulation and organisation.

[2] See e.g. Art. 5.1 b Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation), GDPR, Chap. 2 § 4 the Swedish Patient Data Act (2008:355).

[3] Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act), European Commission, proposal for a regulation of the European Parliament and of the Council on the European health data space, COM(2022) 197 final.

5.8 Information for Prediction

Predictions can support inter-organisational collaboration with a shared view of a situation. In emergency care processes, patients like Alex risk getting stuck in bottlenecks, causing suffering and delayed interventions. Therefore, caregivers need to understand the patient flows.

Solutions for analysing patient flows include the work of Zlotnik et al. [21], who have tested support vector regression (a form of supervised machine learning) used for prediction and dynamic allocation of nurse staffing needs. The test was conducted with data from a 1,100-bed specialized care hospital. Furthermore, Alharbi et al. have tested an artefact that use unsupervised machine learning with data from patients case to identify patients flows, thereby reducing the time needed from domain experts to share their knowledge [1].

Another problem where accurate predictions are needed is on an individual level. For example: Is Alex likely to have to be readmitted in the near future if discharged? Chen el al. [2] have developed a method for applying machine learning to patient case files in order to predict the probability of hospital readmission. Furthermore, Glover et al. [7] have tested how to calculate how likely it is that a patient will not come to a scheduled consultation. Proactive actions were suggested, such as sending text messages or arranging transport. A related solution is provided by Resta el al. [17], who have tested how to use machine learning on case files to predict how long patients will stay in ER. A similar approach has been taken by Jiang et al. [11], but on a conceptual level.

As part of developing and deploying predictive models to prevent hospital readmission, legal and ethical aspects need to be included in both the design and the use of such solutions.[4]

6 Discussion

This study's focus on collaboration in healthcare affected the results in terms of the AI solutions that we found applicable. This focus on collaboration led to that some of the identified problem areas being left without matching AI solutions, to some extent this could be expected. AI is simply not a panacea for all problems. That said, we did expect it to be easier to find, in particular, fully implemented AI solutions, even if our scope was narrow.

Collaboration among actors means that several IT systems are involved—in the studied case, each actor had at least one system on their own. This pushes *RPA* as an approach with much potential. This is also what Davenport & Kalakota [4] have argued with regard to what they refer to as administrative applications. The lack of interoperability causes healthcare staff spending time copy/pasting, faxing and typing. While waiting for improved interoperability, RPA solutions can reduce parts of this workload.

Evident when performing the interviews in the case was that the sensitive nature of health data has so far had a cooling effect on information exchange.

[4] See e.g. art. 25 of the GDPR.

This effect is there for machine learning approaches as well—without training data it is difficult to research and build AI solutions. However, it must be highlighted that *rule-based* approaches do not need training data, which increases their applicability.

In spite of the limited access to health care data, *supervised machine learning* applications have been developed, for e.g. improving registered information and managing information overload. NLP of unstructured clinical data could be further developed for refining information for a new purpose.

The identified solutions relying on *unsupervised machine learning* were used for prediction, both on an aggregated level, such as patient flows, and on an individual level for predicting how patients would respond to different possible decisions.

The need for clear and transparent legal rules as well as ethical considerations in relation to the processing of sensitive data such as health data is crucial. Whether the legislative initiatives from, for example, the EU, such as the proposal for a European Health Data Space, are an answer to this seems likely, but to what extent remains an open question.

Regarding the value of this study, we would like to argue that grounding it in a case study lead to us to solutions that matter. We do not claim to present a complete picture of the existing solutions. We believe that this study has practical use for IT managers in the healthcare sector looking for possibilities, as well as for researchers searching for new territory in the rapidly expanding AI field.

7 Conclusions

In this paper, we utilised a case study to examine if AI solutions can support complex inter-organizational healthcare. Based on interviews with employees at Region Stockholm and Stockholm Municipality we derived seven problem areas—areas that currently hinder collaboration in healthcare. These problem areas ranged from the support of different communication forms to the transfer of information and coordination among care providers as well as the related legal hurdles.

Given the problem areas, we found several existing AI solutions that could help alleviate the problems. While this is encouraging, we also found that there is extensive research in AI for health care, but much less implemented solutions in practical use, particularly for supporting complex care processes.

The next step in the case study is to examine the IT systems closer to see if the quality and type of data are enough to implement some of the solutions within the existing legal and ethical framework.

Acknowledgements. This study is part of the project Data-driven Solutions in Complex Care Processes (DISAL) which is financed by Region Stockholm.

References

1. Alharbi, A., Bulpitt, A., Johnson, O.A.: Towards unsupervised detection of process models in healthcare. Stud. Health Technol. Inform. **247**, 381–385 (2018)
2. Chen, T., Madanian, S., Airehrour, D., Cherrington, M.: Machine learning methods for hospital readmission prediction: systematic analysis of literature. J. Reliab. Intell. Environ. **8**(1), 49–66 (2022). https://doi.org/10.1007/s40860-021-00165-y
3. Communication Platform. https://cuviva.com/en/offer/
4. Davenport, T., Kalakota, R.: The potential for artificial intelligence in healthcare. Futur. Healthc. J. **6**(2), 94–98 (2019). https://doi.org/10.7861/futurehosp.6-2-94
5. Digitala vårdtjänster och artificiell intelligens i hälso- och sjukvården. Technical report, National Board of Health and Welfare (Socialstyrelsen) (2019). https://www.socialstyrelsen.se/globalassets/sharepoint-dokument/artikelkatalog/ovrigt/2019-10-6431.pdf
6. Fast Lappalainen, K., Fors, U., Henkel, M., Magnusson Sjöberg, C., Perjons, E.: Digitalisering inom vård och omsorg : Ett projekt om samverkan inom och mellan Region Stockholm och Stockholms stad. Technical report. No. 21-003, Stockholm University, Stockholm (2021). http://urn.kb.se/resolve?urn=urn:nbn:se:su:diva-196640
7. Glover, M., et al.: Socioeconomic and demographic predictors of missed opportunities to provide advanced imaging services. J. Am. Coll. Radiol. **14**(11), 1403–1411 (2017). https://doi.org/10.1016/j.jacr.2017.05.015
8. Grant, M.J., Booth, A.: A typology of reviews: an analysis of 14 review types and associated methodologies. Health Inf. Libr. J. **26**(2), 91–108 (2009)
9. Hessius, J.: Håll koll på din operation. http://operationskollen.se
10. Iliashenko, O., Bikkulova, Z., Dubgorn, A.: Opportunities and challenges of artificial intelligence in healthcare. In: E3S Web of Conferences, vol. 110, p. 02028 (2019). https://doi.org/10.1051/e3sconf/201911002028
11. Jiang, S., Chin, K.S., Tsui, K.L.: A universal deep learning approach for modeling the flow of patients under different severities. Comput. Methods Programs Biomed. **154**, 191–203 (2018). https://doi.org/10.1016/j.cmpb.2017.11.003
12. Mehta, N., Pandit, A., Shukla, S.: Transforming healthcare with big data analytics and artificial intelligence: a systematic mapping study. J. Biomed. Inform. **100**, 103311 (2019). https://doi.org/10.1016/j.jbi.2019.103311
13. Dictionary by Merriam-Webster. https://www.merriam-webster.com/
14. Murphy, D.R., et al.: Computerized triggers of big data to detect delays in follow-up of chest imaging results. Chest **150**(3), 613–620 (2016). https://doi.org/10.1016/j.chest.2016.05.001
15. Panch, T., Mattie, H., Celi, L.A.: The inconvenient truth about AI in healthcare. NPJ Digit. Med. **2**(1), 1–3 (2019). https://doi.org/10.1038/s41746-019-0155-4, number: 1 Publisher: Nature Publishing Group
16. Refined eHealth European Interoperability Framework. Tech. Rep. Ref. Ares(2017)4754764, eHealth Network, Brussels (2015)
17. Resta, M., Sonnessa, M., Tànfani, E., Testi, A.: Unsupervised neural networks for clustering emergent patient flows. Oper. Res. Health Care **18**, 41–51 (2018). https://doi.org/10.1016/j.orhc.2017.08.002
18. Rouse, W.B.: Health care as a complex adaptive system: implications for design and management. Bridge-Washington-Natl. Acad. Eng. **38**(1), 17 (2008)
19. Schneider-Kamp, A.: The potential of AI in care optimization: insights from the user-driven co-development of a care integration system. INQUIRY J. Health Care Organ. Provis. Financ. **58** (2021). https://doi.org/10.1177/00469580211017992

20. Västra Götalandsregionen: Innovationsdagen 2019 - Administrativ förenkling med hjälp av datoriserade robotar, February 2019. https://www.youtube.com/watch?v=wan1O_tS4Qs
21. Zlotnik, A., Gallardo-Antolín, A., Alfaro, M.C., Pérez, M.C.P., Martínez, J.M.M.: Emergency department visit forecasting and dynamic nursing staff allocation using machine learning techniques with readily available open-source software. CIN Comput. Inform. Nurs. **33**(8), 368–377 (2015). https://doi.org/10.1097/CIN.0000000000000173