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# Advancing Open Innovation in Data-Driven Preventive Healthcare

Marika Iivari*, University of Oulu, Oulu Business School

Minna Pikkarainen, University of Oulu, Oulu Business School

Peter Ylén, VTT Technical Research Centre of Finland

Julius Francis Gomes, University of Oulu, Oulu Business School

Jukka Ranta, VTT Technical Research Centre of Finland

* Corresponding author: marika.iivari@oulu.fi

## Abstract

This study applies open innovation on healthcare policy making in order to explore, how preventive healthcare would benefit from more open processes on knowledge flows in regards to decision making, and what could be done to advance open innovation in the healthcare sector. Especially the development of digital technologies has contributed to opening the healthcare sector, as digitalization has enabled unique ways for generating, collecting, analyzing and sharing health related data. However, healthcare as an innovation system is very different from other industries, setting specific challenges on knowledge sharing and processes.

Based on empirically grounded research through system dynamics on preventive data-driven healthcare, this study explores how healthcare policy making could benefit from more distributed data and knowledge flows, in relation to data collection and analysis, across organizational boundaries, as suggested under the open innovation paradigm. The results of the study suggest that technological and analytical solutions brought by digital technologies have the ability to support faster and better use of data and speed up the distribution of knowledge flows across different city service units in order to create more personalized and tailored services for and their families. However, they are effective in preventive healthcare only if knowledge is systematically carried across organizational boundaries, which highlights the central role of policy makers driving this change.

**Keywords:** open innovation, healthcare, data-driven, preventive, knowledge, decision making

## Introduction

Healthcare as an innovation system differs quite distinctively from other sectors. First of all, state health systems represent a major, in fact, in many cases *the* major, customers for innovations, but these health systems are also extremely complicated and fragmented as customers (Gabriel et al. 2017). Second, health innovation systems are unusual also from the perspective that the health systems as main innovation customers are different from the actual innovation users i.e. the patients and/or citizens (Gabriel et al. 2017). Innovations in healthcare relate not only to medical or pharmaceutical innovations (Ciani et al. 2016), but also to new approaches to prevent illnesses, and promote the wellbeing of people (Gabriel et al. 2017). Indeed, the definition of healthcare innovation has changed drastically over time: now innovations in patient care, wellness or health tech are considered as innovations in healthcare (Francis Gomes and Moqaddamerad, 2016). Digitalization, digital technologies and the use of data have had a major impact also on opening innovation processes in the healthcare sector (Kalis, 2016). For instance, mobile device assisted healthcare, and medical applications are considered to create the next big advancement in the health industry (Balandin et al, 2013; Francis Gomes and Moqaddamerad, 2016). The disruption that the use of data has caused in the healthcare sector, e.g. the availability of biomedical data and the genetic makeup, has even been compared to how the development of ICT changed the society in the past decades (Horgan et al. 2014).

However, the reality is not as rosy as it may sound. Although healthcare data has been made increasingly available for decision making, especially the public healthcare sector is still suffering from the lack of *systematic* use of different types of data (Krumholtz, 2014), which has direct implications on health policies and policy making. In OECD countries, for instance, policy makers and health system managers seek to move towards performance-based governance, but this requires accurate and timely patient data, from actual care to health outcomes and costs (Paavola, 2017). However, at the moment, decision makers, such as public health providers, community level decision makers, city level decision makers and governmental level decision makers, typically do not have any *control* over the design of the data, its formatting or how the data is collected. The opposite is in fact true; the knowledge health providers' base their decisions on, is often severely fractured, disjointed, stored in multi-formats, and not even always in an electronic format (Iivari et al. 2017). Also, how real-time the data is, would be of relevance for decision-making in healthcare. Data-driven decision-making tools have been developed for health policy makers in Europe. However, even at their best, these tools are mainly based on authenticated statistical data that is one to two years old. This kind of historical data decision-makers ought use to identify not only current needs but also to predict *future* needs trends in specific thematic areas. These conditions have resulted in significant challenges for preventive healthcare providers to use valid information for decision making. Preventive healthcare by definition aims at making tomorrow’s decisions based on today's outcomes (Sherrod et al. 2010).

In addition to the use of data for decision making, preventive healthcare is lacking from the systematic distribution of knowledge flows, as characterized in the open innovation paradigm (Chesbrough et al. 2014). Despite increasing interest in exploring open innovation in the healthcare sector that involve such systemic methods of collaboration, there is a lack of studies on open innovation in the public context, where the complexity of healthcare system is one of the biggest challenges  (Wass and Vimarlund, 2016). Health policy making involves courses of action and inaction that impact different institutions, organizations, services as well as funding arrangements in the healthcare system in place (Buse et al. 2012; Dye, 2001). Healthcare is distinguished by the special status of biomedical knowledge in contemporary societies, as well as by experts who have mastered this knowledge (Gabriel et al. 2017). Open innovation in healthcare is challenged by ”the things it has become famous for, including tight control of intellectual property rights and a certain amount of skepticism voiced by doctors and scientists who feel that their problems are so specialised that no one outside of their field could solve them" (Silvi, 2015).

However, public health in general is affected by various kinds of determinants outside the healthcare system, such as economic, social, political and technological factors (Brownson et al. 2009; Buse et al. 2012). Especially in preventive healthcare, these external determinants should be addressed to ensure robustness of public health policies. Policy making in healthcare is often based on intuition rather than evidence and data (Otjacques et al. 2014), because there is a lack of understanding on evidence-based policies (Brownson et al. 2009). The healthcare sector has not widely engaged in open innovation (Wass and Wimarlund, 2016). Yet, there are demonstrable benefits of "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries" (Chesbrough and Bogers, 2014: 17) in the healthcare sector for health policy and public decision making. Open innovation in data-driven policy making can help to change the healthcare industry from treating sicknesses reactively into improving the wellness of people proactively (Clulow, 2013; Iivari et al. 2017). The increase in the amount of and the diversity of information combined with improved storing capabilities for (electronic) data, and analytical tools offer abundant opportunities to all stakeholders in the healthcare ecosystem (manufacturers, regulators, payers, healthcare providers, decision makers, researchers) and moreover, data also enables improving general health outcomes when exploited the right way (Leyens et al. 2017).

Accordingly, to address the gap on the systematic distribution of knowledge flows, and data-driven decision making in the public healthcare sector, the purpose of this study is to empirically explore how preventive healthcare policy making could benefit from open innovation. In this vein we mainly seek to contribute to public policy discussion on open innovation, and ask how **open innovation could advance data-driven preventive healthcare policy making**?

The study is structured as follows. First we set the scene by discussing the literature on knowledge sharing and distribution in the healthcare sector, address the systemic features related to decision making based on that knowledge, as well as address the specificities of data-driven decision making. We will then present our methodological approach applied in the empirical case, present the key findings related to the phenomenon, and conclude our discussion.

## Knowledge-based decision making in the healthcare sector

### Knowledge in policy making

Notions like knowledge sharing or knowledge management, which are closely linked with open innovation, are often applied either intentionally or unintentionally what comes to policy making (Riege and Lindsay, 2006). Knowledge management as a process captures the collective expertize and intelligence internally and externally to an organization, and uses it to foster innovation through organizational learning (Yim et al. 2004). The stronger the knowledge base, the more the policy decisions are supposed to succeed (Riege and Lindsay 2006). "Knowledge" as a conceptual term features in the management literature as a strategic asset, whereas in the healthcare literature similar notions are often expressed with terms as "evidence" or "research" (Ferlie et al. 2012). So, terms like knowledge, evidence, and research are often being used interchangeably. For instance Brownson et al. (2009) identified the missing element for public policy literature is a clear definition of evidence-based policy. Public policies refer to government policies or the policies of governmental agencies. Health policies concern courses of action and inaction which affect involved institutions, organisations, services, and funding arrangements of the healthcare system in place (Iivari et al. 2017). Health policies in practice could incorporate both public and private policies. In addition, the development and deployment of health policies can occur in all levels of public decision making, i.e from national to regional to local levels. Policy makers play an important role in the process of innovation as they also intervene in various phases, with different kinds of consequences e.g. in the market relationships between producers, innovators, users and patients (Ciani et al. 2016).

While policy makers are under constant inquisition from society to improve effectiveness and quality of policy decisions despite limited resources (Keating and Weller, 2001), they are further expected to do so demonstrating better transparency and accountability (Riege and Lindsay, 2006). Riege and Lindsay (2006) assert that clear communication and partnership among involved stakeholders regarding the policy outcomes can be a starting point for better policy formulation through open knowledge management. Policy formulation in the context of healthcare is generally a complex process (Brownson et al. 2009). One cause behind is that public health is influenced by numerous determinants outside the health system. When policy makers are formulating health policies they also need to consider those external elements, such as scientific, economic, social and political forces (Brownson et al. 2009; Buse et al. 2012). Therefore, public health policies have a great impact on the health status of populations in general. Otjacques et al. (2014) have claimed that slightly over half of public health policy makers are well informed by public health data before making decisions, and just half use data only sometimes or occasionally 'never' for making public health policy decisions. Up to 64 per cent of decision makers never perform statistical analysis in making these decisions, and 57 per cent of decision-makers do not use any simulation or forecasting and often only use census data and data from epidemiological studies (Otjacques et al. 2014).

Van Beveren (2003) marks the necessity of stronger cooperation and communication among health entities for better patient centered care. The public sector literature lacks discussion from a resource based view (Ferlie et al. 2012), where resources such as inter-entity-collaboration, open platforms, data, information, data integration, integration capacity, knowledge could be perceived as key policy enablers. Knowledge can be shared, sourced, discovered or created. Unfortunately, often health organizations are observed to obtain knowledge exclusively through acquisition (Van Beveren 2003), while discovery or creation of knowledge within healthcare is a real possibility where ample amount of usable data is available.

**Data-driven policy making**

Public bodies are among the largest creators and collectors of data in many different domains (Janssen et al. 2012). The healthcare sector generally produces globally one of the highest amount of data in different forms (Raghupathi and Raghupathi 2014), where the development of digital technologies, such as Internet of Things (IoT), and forthcoming 5$^{th}$ generation (5G) mobile networks, the prospects are immense for the use of data (Iivari et al. 2017). Mostly discussed type of data are “big data”, which was coined by Cox and Ellsworth (1997) who explained the visualizations of data, and challenges they posed for computer systems. As a concept, big data stimulates extremely and uncontrollably saturated digital contents that are used to generate information, in turn helping in knowledge creation (Lohr, 2012).

Discovery or creation of knowledge, for example, through data mining from huge volume of big data brought together is conceptualized as “Knowledge discovery in databases” (KDD) (Fayyad et al. 1996). While in general, KDD can be applicable for one organization holding a big dataset themselves, this approach is also applicable to putting together rich and heterogeneous dataset sourcing from multiple stakeholders to make sense of a previously untapped knowledge source. Rich and heterogeneous sources of data can offer significant opportunities for researchers, health professionals, and policy makers to "move away from looking at population averages and toward the use of personalized information that has great potential to generate personal, societal, and commercial benefits" (Heitmueller et al. 2014). In the wave of digitalisation, healthcare is transforming from a structured-based data (electronic patient report, diagnosis reports that are formally stored) towards semi-structured (home monitoring, tele-health, IoT devices, other sensor-based wireless devices) and unstructured (transcribed notes, paper prescriptions, discharge records, digital images, communication messages, radiograph films, MRI, CT images, ultrasound images, videos) forms of data (Raghupathi and Raghupathi 2014; Wang et al. 2016). While big data is assumed to impact health sector positively, especially inadequate integration of data in multiple healthcare information systems causes challenges (Wang et al. 2016; Bodenheimer 2005).

Therefore, in data-driven policy making, it is important for decision makers to understand the different types of data sources that may be useful in healthcare related policy making situations. The challenge for public policy making is that big data is mostly in the private sector. Three different data sources are typically used in the big data industries (Brownlow et al., 2015). These are self-generated data, custom provided data and free available data. The value of self-generated – i.e. personal data is growing (Schwartz 2004). Personal data can generally refer to information generated by an individual, which is increasingly driving healthcare policies as well (Iivari et al. 2017). Citizens want to receive more and more personalized and improved care based on their personal data, which impacts the healthcare system in a way that data and technologies allow patients to get care outside hospital walls, to control and share their health information to other stakeholders in the healthcare ecosystem (Gabriel et al. 2017, Gaskell 2017). Digitalization has therefore had a major impact on opening the innovation processes in the healthcare sector (Kalis, 2016). Governmental organisations typically collect personal data such as taxes, residence and date of birth; healthcare organisations maintain a variety of health records; businesses collect client data, shopping behaviour, transactions, receipts etc. (Ericsson, 2013). Free and/or open data in policy level decision-making (Janssen et al. 2012) could involve e.g. traffic data, weather, geography, tourist information, statistics, business, public sector budgeting, and performance levels, policies and inspection (food, safety, education quality etc.) (Janssen et al. 2012). Some examples show the open access of publicly funded data has offered great returns from the public investments providing policy makers data that is needed to address complex problems (Arzberger et al. 2004). It has been claimed by Janssen et al. (2012) that open data has no value in itself; it only becomes valuable when used. In this context however, little is known about the conversion of public data into services of public value.

**Systemic decision making**

Decision making environments are dynamic in the real world, and often tacit knowledge focused (Yim et al. 2004). Knowledge-based decision making that is supported by systemic thinking enables proactiveness of decision making. When public health is concerned, it is important for policymakers to get accurate and real-time information in order to understand different dimensions of healthcare related problems, such as social care, and propose effective solutions for tackling them (Nieminen and Hyytinen, 2015). However, if we think the complexity of health care related issues it is not even possible for one person to search and read enough information to guarantee robust information for decision-making. This is further challenged by the fact that even though healthcare data has been made increasingly available for decision making, public healthcare is largely suffering from the lack of systematic use of different types of data (Krumholtz, 2014). Foresight is one approach among others that helps policy makers to strengthen the participatory, interactive and strategic elements of evaluation (Fetterman, 2001; Patton, 2011, Nieminen & Hyytinen 2015). Foresight can be identified as ‘a systematic, participatory, future intelligence gathering and medium-to-long-term vision building process aimed at present-day decisions and mobilizing joint action’ (Georghiou et al., 2008, 11).

In order to improve the quality of care, efficiency and coordination, policy making and health system management is moving towards performance-based healthcare governance (Paavola 2017). However, to enable performance-based governance, accurate and timely patient data is required, ranging from actual care to health outcomes and costs (Paavola, 2017). However, at the moment, the knowledge health providers' base their decisions on, is often severely fractured and fragmented, stored in various, also in manual, formats (Iivari et al. 2017). These conditions have resulted in significant challenges for preventive healthcare providers to use valid information for systemic decision making. It is not of assistance to policy making that although there is increasing academic interest in exploring open innovation in the public healthcare sector that would involve system level methods of collaboration, in order to make sense of the complexities of the healthcare system (Wass and Vimarlund, 2016). Health policy making involves courses of action and inaction that impact different institutions, organizations, services as well as funding arrangements in the healthcare system in place (Buse et al. 2012; Dye, 2001). Here, data would support the redesigning and evaluation of new models for healthcare service delivery, for instance, thus contributing to the discoveries and evaluations for new treatments. However, “encouraging the uptake of the most efficient and effective frameworks and practices to enable the collection, storage and use of personal health data to improve population health and to improve the effectiveness, safety and patient-centeredness of health care systems remains a significant policy challenge in many OECD countries” (Paavola, 2017).

As complex and dynamic systems (such as the healthcare system in our case) are constantly in a change and involve an enormous amount of impact indicators and within-system feedback loops, a dynamic approach is needed to able to address the complexity (Hargreaves and Podems, 2012). All approaches to strategic decision-making and management have both benefits and challenges. For instance in many cases decision-making is still based on fragmented information which means that the comprehensive information on the environment and its change, as well as an understanding of wider short-term and long-term impacts, are often lacking in policy level decision making (e.g. Loorbach and Rotmans, 2010). Therefore, open innovation through its key approach to knowledge distribution and inter-organizational knowledge flows would have great impact on advancing the effectiveness and impact of policy making especially from systemic perspective. Though driving towards increasingly porous innovation systems, knowledge i.e evidence and data should be generated more openly and in collaboration with external parties. Policy makers need to acknowledge that also healthcare related data can come from anywhere, also through self-generated data by patients, needs of the patients and users should drive innovations in healthcare, coupled by the knowledge of practitioners (Gabriel et al. 2017, Iivari et al. 2017, Bullinger et al., 2012). According to Gabriel et al. (2017) open innovation initiatives in the healthcare sector would contribute to more efficient use of resources and enabling faster adoption and diffusion of healthcare innovations. Another objective is to contribute to innovation processes through deeper understanding of health systems as well as the needs of patients or citizens. In political terms, open innovation should make health innovations more democratic through demand-driven approaches.

## Research design

**Data collection**

The empirical data utilized in this study was gathered within a European Commission H2020 project on the use of meaningful data for healthcare policy making. The current study is based on qualitative, semi-structured expert interviews with regional public bodies and city level healthcare policy makers in the province of Northern Ostrobothnia, Finland, during Spring 2017. The focus of the interviews was to investigate how data is currently being utilized for public healthcare policy making, and what implications different types of data, information and knowledge sources have on policy making. The interviews were conducted in order to build a preliminary understanding of the phenomenon in question, and what kinds of data-driven needs, barriers and future opportunities relate to preventive healthcare in particular. The specific case identified for preventive healthcare decision making was the mental health of young people.

Eight representatives from different city and municipal organizations were interviewed in six different interview sessions. The interviewed were conducted in the native language of the interviewees, i.e. in Finnish. All interviews were recorded, transcribed and translated into English, and thematically analysed (Boyatzis 1998).

Table 1. Interviewed policy makers

| **Role** | **Date** | **Duration (h:mm)** |
|---|---|---|
| Finance Manager<br>Development and Quality Manager | Feb 27th 2017 | 1:02 |
| Director of Healthcare and Social Welfare | March 20th 2017 | 0:53 |
| Head of Health, Social and Education services | March 22nd 2017 | 1:24 |
| Director of Healthcare<br>Director of Social Welfare | March 22nd 2017 | 0:59 |

| | | |
|---|---|---|
| Director of Education | March 28th 2017 | 1:06 |
| Director of Joint Municipal Authority | April 10th 2017 | 1:33 |

**Data analysis**

In order to further advance knowledge distribution and decision making in preventive healthcare, a system dynamics modelling workshop was organized in May 3rd, 2017, where all interviewed parties were invited to collaboratively validate, visualize and simulate the interview findings. System dynamic modeling is a method that combines both tacit and deliberate knowledge of individuals and sub-groups within organizations, where alternative actions are used to simulate and predict future outcomes (Woodside, 2010). A system dynamics (SD) model describes complex connections between multiple elements in different levels, in addition, it explains dynamic processes with feedback in the system (He et. al 2006). For policy analysis and recommendation, SD models help predict complex system behavior under various "what-if" scenarios (Mohapatra et al. 1994). SD modeling techniques challenge narrow views and encourage seeing the big picture both in time and space, that is, considering outcomes both in the short and long run and across organizational boundaries. The models foster communication between different views enabling reflective and collaborative solutions. All of these features of SD modelling are building blocks of innovations, and eventually lead to better decisions.

More specifically, we applied group model building (Vennix, 1993; Michaud, 2013) with focus on qualitative modeling as the tool to facilitate discussion and sharing of knowledge and understanding among the different decision makers. This tool was chosen, as it allows slicing and presenting complex systems on a suitable level of abstraction in order to identify the points of interconnections between knowledge flows that otherwise could fall in different silos in organizational boundaries, both internally and externally to healthcare organizations. Moreover, group model building stands apart from other modelling techniques by the direct involvement of decision makers, stakeholders, and topical experts. It has two primary aims; elicit input from the participants to construct and validate a model; and use the modelling process as a learning process for the participants as they share knowledge with each other and reflect their mental models with the model under construction. The two aims share the underlying objective of aiding decision making. We employed group model building to facilitate participation of a heterogeneous group of actors involved in various areas in preventive healthcare, including those of the social welfare, healthcare, education and other sectors, i.e. service units. Through a set of methods and work practices, we elicited information and insight needed for system dynamics models, while helping decision making as a process on its own.

Therefore, we see that system dynamic modelling is one of the key tools in driving open innovation in the healthcare sector, providing evidence-based support for policy makers to promote the purposively managed, distributed knowledge flows across the silos of public decision making.

## Results

The research results were categorized under two themes. The first includes current decision making and data-driven knowledge management practices in relation to preventive healthcare, and mental health of young people. The second one presents the knowledge requirements and needs that policy makers have for producing the healthcare policies of the future. These themes emerged as the most important factors in discovering the role of open innovation in data-driven healthcare policy making.

**Preventive decision making**

Organising resources for preventive mental healthcare services for young people was highlighted as the most crucial challenge for decision-makers. In this context, substance abuse and unemployment prevention emerged as very close concerns for decision-makers. Thus, mental health is a complex and multileveled case, and data required for policy making requires the use, analysis and visualisation of heterogeneous types of data.

However, the research results reveal that as a starting point, there was high variation in the way that the interviewed policy makers were using digital systems in current or historical evaluation of healthcare situations and cases. Some of the interviewed policy makers did not have any digital tools in use in the decision making process. In fact, for some of them, a typical situation is that the policy makers are having secretaries who are preparing the information for them based on the information that can be found from Internet and statistical data. *"most often we use the information about what has happened, not information what is most likely going to happen"*.

> *"Real-time data? Capacity, situation, daily, customer flows, use of spaces etc. Useful for the organiser who is responsible for the entity. Production unit, individual follow-up. Intensive care, customer-centric impact. Long term data"…*

> *"The real-timeliness of data matters, in the wellness report there is a lack, since it's updated every two years. We would need information from the on-going year… Something could come faster… Some have data on booklets, some have manual data.. How does information*

*travel between different actors, do we buy child protection and substance services and elderly services. Could be even faster, a substance client needs information right away".*

The systemic evaluation based on inter-organizational knowledge sharing, including qualitative and quantitative approaches, was seen as an approach that would provide the needed information about the past and current state of the system and the health status of individuals, which was referred to as the digital footprint. However, this is not yet the case in current decision making models. In our case, system dynamic modeling provided the needed evidence of dependencies that follow from actions taken. The systemic evaluation will also support redirecting policy instruments to better respond to the needs of a shaping health care environment, and to show the overall results and outcomes of potential decisions, in order to support more preventive and predictive decision-making.

An interesting notion from the interviews was also the problem with scarce data from social services compared to data from health services. Legislation is one key challenge there, as of now, in many situations, laws prevent the personal identification of individuals, as well as the use of data across organizational boundaries, such as from education or social services into the use of healthcare decision makers. Moreover, healthcare data mainly consists of numerical, quantitative data, and qualitative data that would be most relevant to preventive actions, is lacking.

*"We have customer data missing in the social services side, quita a lot actually. Like from private clients. Kids, youngsters, families with children, working people... We have quite a lot of data related to use, but no predictive information really."*

The interviewees pointed out that this is an issue which needs development, as preventive mental healthcare services are a much wider concern for the society, than e.g. diabetes. It was said, that if a person has diabetes, that concerns just the individual, but if a person has mental health issues, that concerns also immediate family, relatives, school, work and a person's ability to contribute to society and economy e.g. in the form of employment and taxation.

**Knowledge distribution in decision making**

Separating knowledge distribution and knowledge management from preventive decision making were seen as two sides of the same coin. However, based on the use of data, some key issues were identified.

> *"The problem is that cause-consequence isn't that clear. Education and culture plus wellness services, why does it show that the red services have increased? There has also been a lot of leukaemia and premature birth cases. If we rely too much on raw data, we can draw false conclusions."*

> *"Integrating research results would be useful. We would need more, like impact evaluations."*

One challenge of the evaluation leading to actual decision-making is also analyzing the interdependencies and interactions within the healthcare in connection to social care system, as well as between the system and environment. In our case it was also noted that, *The information is shared in silos and it is owned by different actors. It would be great to understand for instance what services has been offered to one individual. Perhaps a person has got a disability diagnosis later. Perhaps he has been going through the whole school system and his situation is never investigated"*

*"Looks like that with youngsters, we have this group that doesn't put effort into studying academic subjects, there should be more of these apprenticeship type education for those who don't read. Those that have been under special needs education, have received better scores, but they fall out when they no longer get support. Those that are worse than normal students, don't get into schools… There could be developmental delays, behavioural problems, substances, child protection.." This information is divided and behind different authorities. What services have been offered to one person, for example … Has this person gotten a developmental diagnosis later. Have they just surfed through school so that they have never been examined? Now they have been guided to employment services and never received (healthcare) services that they would have been entitled to. These kind of things should be summed up"*.

Among the policy makers that we interviewed, foresight was seen as a way to generate information about alternative futures in a system by analyzing trends and drivers that cause changes in the system.

*"Scenarios would be interesting. If people for instance loose some reimbursement or state aid, it might have some long term social impact that we do not see now"*

Another key source of external knowledge was seen to emerge from the private sector, such as from schools, church, sport centres, clubs, libraries, youth centers, private sports facilities, cultural facilities and so on. The way public decision-makers are collaborating with the private sector and third parties is varying much between the regions, but all of the interviewees acknowledge that important information could be gained from membership registries, and especially from schools. However, access to private sector data is an issue, as so far, as here as well, the legislation prevents the identification of an individual. However, it was stated that for preventive care, that is exactly the need, in order to capture those youngsters before they develop serious mental conditions, substance abuse or issues with abuse, crime and so on. Active collaboration with schools was highlighted, and schools also have access to collaboration with various kinds of 3rd parties.

Not only access and sharing of knowledge, whether public or private, was an issue but also the depth of it: *"the information is too general level at the minute" "with the current data we can make false conclusions"*. Evaluation approaches will be in the future combined with foresight to generate detailed information on the development of a phenomenon at systemic level. This approach will support operational target setting by providing information of the potential impacts of planned actions related to decision, and how the policies could impact people's mental health or wellbeing in the near and longer future.

Foresight is also addressing the challenge of making sense of rapidly changing decision-making contexts and aiding formulation of commonly shared future visions among central actors in the system. This is particularly important in the case of mental health in which it is crucial to indentify the risk indicators and to react early in order to help individuals when things are still possible to be affected more easily and with smaller costs: *"we would need the preventive and predictive system that helps us to see the future"*

To synthesize the findings from the interviews and system dynamic modeling workshop, the key factors in data-driven healthcare policy making are illustrated in the Figure 1 below.

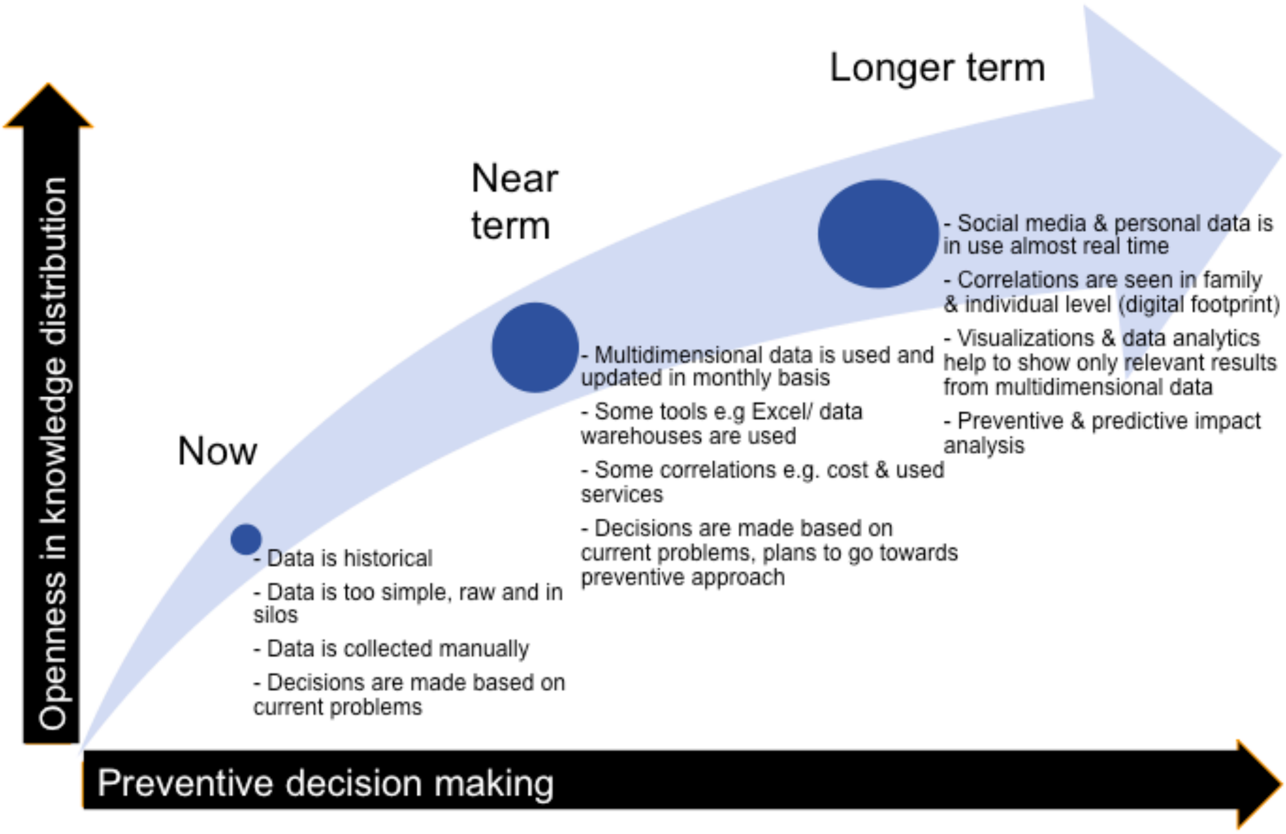


Figure 1. The development of data-driven decision making

The key factors are increasingly open and more widely distributed and utilized healthcare data, coupled with increasingly future oriented, predictive and causation-supported data as the basis of knowledge-based decision making. Preventive stance to decision making is not possible without access to various types of data, but timeliness and accuracy of that data is equally relevant. The reliability of data for policy making can be supported through accessing data from various sources beyond single organizational domains, as mental health as the case especially requires as open and as distributed flows of knowledge, in order to produce as preventive and as tailored policies and services as possible.

## Discussion and conclusions

Through exploring the utilization of different kinds of data in policy making, this study highlights the complexity of decision-making in the healthcare sector (Gabriel et al., 2017; Wass and Vimarlund, 2016). Focusing on single type of data from a single sector cannot truly uncover the systemic nature of relations and dependencies, which not only policy makers but healthcare practitioners alike need to acknowledge.

Here, the technological and analytical solutions brought by digitalization have the ability to support faster and better use of data for creating more personalized and tailored services for the needs of individuals and their families. However, they are effective in preventive healthcare only if knowledge is systematically carried across organizational boundaries. Enabling and supporting distributed knowledge flows for policy decisions is only one preliminary step in the road to data-driven policy making. Data analysis and visualisation are essential elements in turning data into information for decision-makers. Moreover, as traditional data concentrates on current and historical statistics whereas decision-makers increasingly require alternative futures and long term impacts of the decisions made, there is a definite need further research in integrating rich data to other tools for healthcare policy development. Decision-making in healthcare sector has direct and indirect implications on individual patients, health professionals, health businesses as well as the society as a whole. Our results show how open innovation could advance this further, as currently, decision making still mainly occurs in individual silos, and knowledge does not travel across organizational and departmental boundaries. Openness in the distribution of knowledge at the moment makes preventive decision making challenging, as decision makers do not have access to systemic level, analyzed data, or the data becomes available only after a delay due to processing by other official statistics collecting organizations. Therefore, data-driven decision making is always slightly retrospective, especially when more and more data sources are identified and utilized for drafting specific decisions or policies. However, only through reigning the tacit knowledge with the support of suitable methods, such as system dynamics, and the right types of data, it can lead to better preventive decision-making.

This study provides empirically grounded findings on how different types of data and knowledge sources, are and should be distributed across organizational boundaries. By looking preventive mental healthcare of young people, we explored what type of knowledge is distributed across city service units, and what implications these data-driven decisions have had on healthcare policy at systemic level. Thus this study contributes to open innovation in the public context, and open innovation in healthcare. We seek to contribute to the discussions how open innovation paradigm could advance the development of (better) data-driven policies, and support knowledge management and decision-making in public organizations. We also contribute to data-driven decision making. Alike, this study also addresses issues in relation to innovation systems literature through addressing the healthcare system.

The main practical implications of the study relate to the opportunity to increase knowledge on the applicability of open innovation in the healthcare sector, and how this can be advanced in practice through systems thinking, and system dynamic modeling as a methodological approach. Thus, the ways in which open innovation as a process of distributed knowledge flows across organizational boundaries can increase the effectiveness of preventive healthcare can be examined through participatory group model building, which was applied in this study. In this way, this study also highlights that the greatest barriers to advancing open innovation in healthcare relate to distribution of knowledge rather than the availability of healthcare data as such. Without breaking the silos, and allowing knowledge to flow between different service units internally to public healthcare organizations, but also between public and private sector, preventive actions cannot have the strongest impact on the health of the society and especially our youth. Here, public policy makers have a key role in driving this change and opening the healthcare sector further.

Although the research methodology utilized in this study is its strength, it is also the weakness. Through such a strong qualitative stance, national system level correlations and statistical cause-consequence analyses cannot be made. Although the phenomenon itself, preventive healthcare, especially in the case of the youth, is something that touches most modern, advanced societies, the data in this study includes also the largely experiental, tacit type of knowledge, which is difficult to quantify.

However, these challenges also lead to interesting future research directions. Methodologically, a longitudinal approach on following how policy making is changing with the use of more predictive types of data, supported by systemic, collaborative decision making methods, would allow a more systematic analysis on how open innovation paradigm is spreading in the healthcare sector, especially in public healthcare providers, not just in private corporations. Moreover, it would be interesting to study how the mindsets of policy makers are changing with the use of open innovation practices and system dynamic tools, and how public healthcare providers embrace openness in order to advance the wellbeing of citizens as a whole.

To summarize the study on how open innovation could advance data-driven preventive healthcare policy making, we see it as two-fold; first, increasing understanding on the importance of freer flows of knowledge across organizational boundaries for better healthcare is the preliminary step. Second, with appropriate tools, such as system dynamics, we are able to concretize this knowledge into actionable, usable relations and correlations. Only with proper understanding coupled with right tools, policy makers are truly able to utilize the right types of data in preventive decision making.

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