Chapter xxx

Network orchestration and system dynamics modelling in developing innovative decision support systems for policy makers

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The decisions on public health policies have great impact on our society and citizens. These decisions made by policy makers are typically driven by various types of continuously changing and interlinked determinants, such as economic, social, political, and technological factors. In this dynamic setting, it is not possible for one person, or even for a team, to understand the whole system, and all cause-effect relations. Therefore, there is a need for data-driven decision support tools.
Here, attention is turned to the potential of system dynamics (SD) modeling and innovation network orchestration for developing such tools. In the book chapter, it is shown how orchestration of a network and the use of system dynamics modeling (that makes visible the causes and effects of systemic challenges) come together in relation to developing an innovative data-driven decision support system for policy makers.

1. Introduction

The healthcare system, and public health policies have great impact on overall health and wellbeing of populations (Brownson et al. 2009). Health policies address courses of action and inaction that affect involved institutions, organizations, services, and funding arrangements within particular healthcare systems (Dye 2001; Buse et al. 2012). Initiating and managing successful policies in shaping health systems calls for continuous network orchestration, i.e. "purposeful actions" […] to initiate and manage innovation processes for value creation and capture (Dhanaraj & Parkhe 2006, 659; Hurmelinna-Laukkanen & Nätti, 2017). There are numerous studies on orchestration within different domains (for overviews, see e.g., Möller & Rajala 2007; Hurmelinna-Laukkanen et al. 2011). These studies often concentrate on structural issues, the aims set for networks, and orchestration activities required in achieving these aims. In many cases, the discussion assumes some firm to be the orchestrator. It is more challenging to find studies where orchestration is connected to actions targeted to systemic change. Yet, the principles of network orchestration are applicable also here.
Various rapidly changing determinants (e.g. economic, social, political, technological) outside healthcare affect and drive public health (Brownson et al. 2009; Buse et al. 2012). These external determinants need to be embraced for making public health policies robust. However, evidence-based policies are not optimally utilized in healthcare, most notably due to inadequate understanding (Brownson et al. 2009) and quantification or projection of health problems (Murray & Lopez 1996). Instead, policies are often slow, reactive (Nieminen & Hyytinen 2015), and base on intuition, rather than on evidence and data (Otjacques et al. 2014). A possibility to respond to these challenges is to employ orchestration

and foresight; participative process that helps policy makers to jointly build medium or long term vision for analyzing future possibilities (Nieminen & Hyytinen 2015).

Public health policies are usually formulated for total populations (Buse et al. 2012). This sets some specific requirements on orchestration in the development of evidence-based policies. Broad policy decisions are, in principle, based on anonymized data collected from citizens. However, continuous systemic analysis of abundant public health and healthcare data (e.g. health big data, rich data) becomes challenging without proper modeling (Raghupathi & Raghupathi 2014). In this context, the model for systemic analysis of public health and healthcare data should be adequately broad to encompass multiple dimensions affecting the system, and to help decision makers to see potential short- and long-term impacts of alternative decisions, such as those related to resources and finances allocated in different regions. In fact, there is a need for quite a dynamic approach and related tools —e.g. system dynamic modelling (see Forrester 2007; Sterman 2000)—to allow policy makers to understand these issues better (Hargreaves & Podems, 2012).

Relying on network orchestration (Nambisan & Sawhney 2011; Dhanaraj & Parkhe 2006; Hurmelinna & Nätti 2017), system dynamics, and foresight literatures (Forrester 1996; Forrester 2007; Sterman 2000; Hyytinen et al. 2014), we explore the potential of system dynamics (SD) modeling as a tool to be used in connection to innovation orchestration in the context of evidence-based public health policy-making. We explore how orchestration of a network connects to system dynamics modelling when developing an innovative data-driven decision support system for policy makers. Towards this aim, we approach public health and healthcare as a "system" and model its dynamics. We examine these issues in Finland, where a health and welfare reform has been taking place, requiring continuous policy actions and decisions at different levels (e.g. in ministries, regions and municipalities). This reform depicts a setting, showing the relevance of network orchestration and generating applicable tools regarding systemic change.

2. Background - System dynamic modelling for innovation network orchestration in policy making

The overview above forms the basis for subsequent discussion. In the following, we discuss here the premises of system dynamics and innovation network orchestration to ground more context specific considerations.

2.1 System dynamics and group model building

System dynamics has its roots in control engineering and simulation analysis, applying innovatively the methodologies utilized in mechanical, chemical, and electrical systems (Forrester 1961). Adopting this view, the methodologies can be transferred to model, for example, economic, social, and ecological systems. A system dynamics (SD) model describes the complex connections between multiple elements at different levels. In addition, it explains behaviors of dynamic systems, using the structure of those systems as the basis (Forrester 1996; Forrester 2007; Sterman 2000). SD modelling techniques challenge narrow views and encourage seeing the big picture both in time and in space. The qualitative causal models characteristic to SD modelling visualize complex dependencies without requirements for mathematical expertise, and foster communication between different actors and stakeholders, thereby enabling reflective and collaborative solutions. These features of SD modelling create ground for innovations and eventually lead to better decisions. Hence, we view SD as one potential tool that enables the emergence of innovative data-driven decision support solutions.

What makes SD modelling particularly lucrative tool is that beyond modeling, analysis via simulations allows gaining understanding and insights of systems that have dynamic complexity beyond what human brains can manage (Sterman 1989). In particular, delayed, cumulative, and feedback-related phenomena are difficult to grasp without suitable methods for presentation and analysis. These phenomena are specially challenging to comprehend accurately, when they cross boundaries between organizations, areas of responsibility, or geographical regions (Sterman 2006). As a part of the healthcare policy making process, SD model helps predicting complex system changes under various “what-if” scenarios (Mohapatra et al. 1994).

In our context, the primary interest lies in group model building (Vennix 1996; Michaud 2013) as a tool for orchestrating data-driven decision support system innovation. It has the ability to facilitate discussion and sharing of understanding between different stakeholders of a complex organizational and social system. The qualitative modeling formalism allows presentation of complex systems on a suitable level of abstraction, and subsequently allows seeing the interconnections between areas that often fall in different silos of organizations, or in entirely different organizations (Senge 1990; Stroh 2015).

Group model building has two primary aims: 1) gathering input from participating experts and stakeholders used to construct and validate a model, and 2) using the modeling as a learning process for the participants through knowledge sharing and reflection of their mental models with the model under construction. Both aims have a shared objective of enhancing decision-making. The constructed model and simulation analysis provide a set of results that allow comparison of alternative strategies and scenarios, and thereby offer insight of the behavior of the system under consideration. Group model building stands apart from typical modeling processes in terms of the direct involvement of the decision makers, actors, topical experts, and stakeholders. Participation in the modeling process builds understanding of the structure of the system and the underlying characteristics that lead to the observed behavior. Participation also strengthens the understanding of the model and, thereby, trust in it. It also improves the ability and willingness to implement the policy suggestions drawn from the discussions and analyses. Group model building can be implemented in a smaller group of core decision makers or the approach can be extended to the affected population (Hovmand 2014; Frerichs et al. 2016). Therefore, it may well emerge in connection to innovation network orchestration.

2.1 Network Orchestration

Whereas the SD modelling allows building of understanding, network orchestration can be combined into it to facilitate decision-making and the related processes in practice. As suggested above, network orchestration—and innovation network orchestration in particular—comprises different activities that allow central actors to steer the network, its members, and goals towards preferred directions.

In systemic contexts, there is a demand for a network orchestrator to have visioning capability to see the direction of change, and the type of policies that are likely needed in order to respond to that development. Likewise, the actions of setting the agenda (opportunity identification and goal drafting) and coordinating (promoting and administrating interaction besides knowledge transfer) are relevant to ensure the efficiency and smooth operation of critical undertakings (Hurmelinna-Laukkanen et al. 2011; Sabatier et al. 2010). Creation of positive atmosphere, common agenda, and information sharing from different perspectives requires systemic approach that enhances commitment between the actors (Ring & Van den Ven 1994). Connecting closely to the premises of SD modelling and its advantages, innovation network orchestration also involves knowledge mobility, which can be defined as the ease with which knowledge is shared, acquired and deployed among the innovation network actors (Dhanaraj & Parkhe 2006). A set of practices, such as generating common platforms for information exchange, resonates with group model building. In heterogeneous networked innovation context, efficient transfer and exchange of data and knowledge (Crossan & Inkpen 1995; Moenaert et al. 2000; Hurmelinna-Laukkanen & Ritala 2010) and encouraging documentation (Moenaert et al. 2000) are continuously needed. Communication is particularly important (e.g., between policy makers and other actors of health systems) in order to promote and motivate organizations to identify their roles and expectations in the network (Bessant & Tsekouras 2001).

In this context, the orchestrator has, moreover, often a role to support work and responsibility identification and sharing between the actors (Möller et al. 2005). Network stability and innovation appropriability need to be secured so that the pursued outcomes can be achieved without unnecessary disturbance (Hurmelinna-Laukkanen & Nätti 2017).

Considering the features of network orchestration and its connections to SD modelling, it can be suggested that network orchestration and SD modelling can form an entity, where orchestration is utilized to promote generation of decision support systems. The required tools can, on the other hand, be derived from SD modelling. Decision support systems built on these elements can be highly valuable for developing and (re)formulating health policies.

However, as literature that would combine these views and take them into the healthcare and health policy context is still relatively scant, we next turn to empirical evidence to explore these issues further.

3. Research design

In this study, we explore SD modelling and network orchestration in the case of preventive mental health for young people. Kessler et al. (2005) notes that half of those who will develop mental health issues show symptoms as early as by the age of 14. The time between prenatal development and early adulthood is crucial for the brain and mental development. Policy improvements and resource investments in preventive services and early intervention programs can significantly impact school drop-out, homelessness, seclusion, addiction to harmful substances and unemployment. The World Health Organization (WHO) defines mental health as "a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community". So, here, preventive mental health refers to the approach that will incorporate preventive services and make it possible for early intervention to improve general populations' mental health. The case provides a suitable empirical context for exploring MIDAS platform's analytical depth and dynamics through numerous variables, as mental healthcare is a systemic phenomenon due to increased costs in various domains of the economy (Iivari et al. 2017).

We collected empirical data by consulting key decision makers through nine semi-structured interviews (Table 1). Interview data was transcribed and thematically analyzed (Boyatzis 1998). Based on the analysis, four workshops (Table 2) were organized to deepen knowledge on the needs, barriers, use and opportunities of data in health policy development (Figure 1). Both interviews and workshop events took place in two iterations. The first round of data collection took place during Autumn-Spring 2017, the following iteration took place in Autumn 2018. These iterative approach was adopted to validate our initial findings and concretize the causal relationships identified for the SD model.

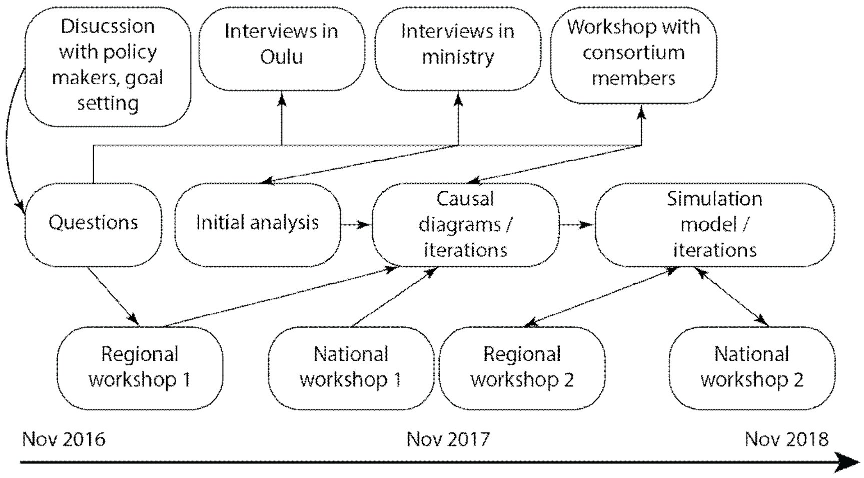

Figure 1. Research Process

In promoting the discussion, the principles of both innovation network orchestration and SD modelling were employed. Organizing of the workshops represented network orchestration activities along coordination, agenda setting, mobilization and knowledge sharing (see Dhanaraj & Parkhe, 2006; Hurmelinna-Laukkanen et al., 2011). We relied on group model building (Vennix 1996; Michaud 2013) to facilitate participation of heterogeneous actors involved in various areas of the social welfare, health care, education and other sectors. We utilized a set of methods and work practices both to elicit information and insight needed for system dynamics models, and to support decision making as a process on its own.

Table 1 Interviews

Role	***Date***	***Duration (h:mm)***
Finance Manager 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 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
Head of Health, Social and Education services Director of Healthcare and Social Welfare	November 8th 2018	1:03
Specialized psychiatrist, public health researcher	November 14th 2018	0:40

Adjunct Professor, Longitudinal epidemiological researcher in the field of neuropsychiatric disorders in children, adolescents, and adults.	November 19th 2018	0:40

A rapid prototyping approach was used while comparing and validating the results. The work was started at the municipal level, the results were then presented and compared in a national level workshop, and then reflected back to municipal level. A rough model based on the interviews was constructed and utilized in workshops. Focus of workshops varied based on decision-making level. On municipal level the focus lied on specific policies and social services provided, while on governmental level, legislation was addressed.

Table 2 Workshops

Workshop	***Date***
Regional workshop 1	May 3rd 2017
National workshop 1	November 3rd 2017
Regional workshop 2	November 7th 2017
National workshop 2	October 12th 2018

The first workshop was arranged with Northern Ostrobothnia's (a region in Finland) municipal officials. Topics were selected based on interview findings, and a causal model was used as a basis for discussions, see Figure 1. Starting from a rough model, the participants discussed the relevance of contents of the model to identify relevant determinants. Then stakeholders linked to the system were discussed to complement the causal diagram. Potential data sources were suggested to facilitate quantification of the causal model into a data-driven decision support tool simulation model.

The second workshop was arranged for national level actors. The participants included officials from different ministries, such as Social Affairs and Health, Economic Affairs and Employment, Finance, and Ministry of the Environment, with National Institute for Health and Welfare, municipal officials (different from the first workshop), and The Finnish Association for Mental Health. Similar to the first workshop, a model presenting causal relations between different areas of society, and a simulation of service allocations were presented to initiate the discussion. From those thoughts, four working groups selected an objective on preventive mental health, and worked towards identifying factors that affect the objective and such data that would measure and fulfil the objective. The second workshop was more focused on discussing how impacts of social problems propagate across different responsibilities in government, i.e., how decision makers in silos can inadvertently make harmful decisions from systemic perspective while fulfilling their own objectives.

The third workshop was again with municipal level actors. The systemic themes related to mental health of youth were elaborated further with different experts from those regional authorities that participated in the first workshop. The participants consisted of education and cultural services, and welfare decision makers working in the area of mental health specifically. The purpose was to gain deeper understanding of the decision-making processes regarding mental health in reflection to systemic issues identified in previous workshops. Again, previously developed causal and simulation models were presented at start. The workshop addressed policy making from service blueprint perspective (https://www.innokyla.fi/web/malli111516), contributing to identifying specific points needed to drive systemic change in health policy making.

The forth workshop involved the national level stakeholders who also participated in the second workshop to validate the development of the SD model. During this workshop, multiple population stories were developed that reflects various aspects health policy making, that can be developed into SD models for policy formulation.

The results from this iterative research process (Figure 1) provided us the foundation for creating a SD model. In the workshops, we drafted an initial simple SD model to visualize, simulate, and validate findings for policy making, and further developed the causal and what if relationships between different elements of the data-driven decision support system after each workshop. Through an interview and workshop process, the expertise of involved actors was used to develop the causal model that links various aspects of society and municipal government. The resulting model is a first step towards creating and implementing the tool that targets to create innovation that allows policy makers to gain accurate foresight on the impact of their planned actions by utilizing data from various sources.

4. Results

Identification of data sources is an important issue for data-driven decisions and policy making. Relevant data sources can be identified only when there is a systemic understanding on the cause-effect relations. In particular, when the focus is on preventive action, the data used in decision-making needs to cover underlying issues that lead to the eventual problems, that is, predictive data instead of indicators of current problems. In our case, system dynamics modelling combined with network orchestration provided a useful route towards understanding of the problem, and identifying cause-effect relations in mental health. We created a SD simulation model highlighting six major dimensions identified: family, intoxicants, wellbeing, freetime activities, school and early education, and studies and employment (Figure 2).

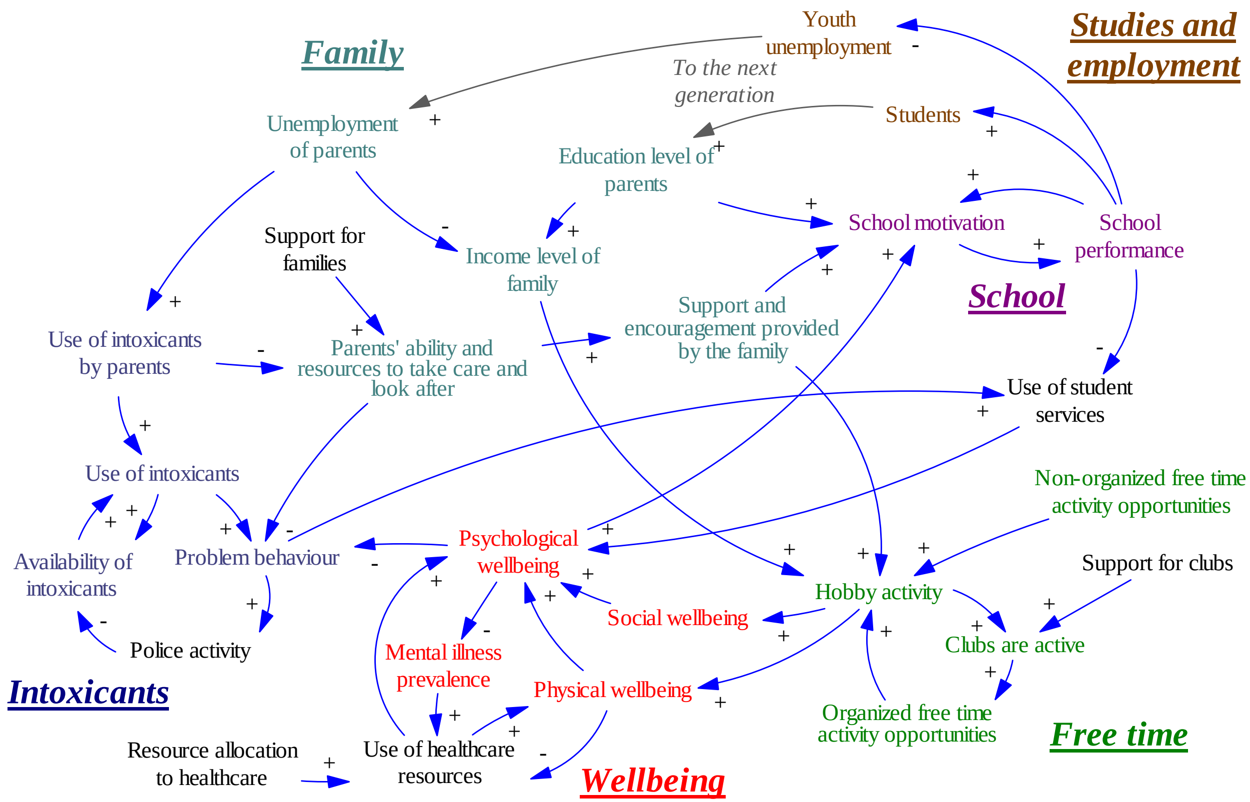

Figure 2. Systems thinking model linking different areas of society and services.

The modelling procedure was considered as a useful tool for initiating and supporting discussions between stakeholders of differing backgrounds, and to visualize the potential future impacts of decisions related to the young, from different perspectives across different sectors. It was acknowledged in the workshops that "We would need the preventive and predictive system that helps us to see the future."

Additionally, the SD model and decision support simulation carried out as a networked activity showed how systemic dimensions correlate with each other and eventually affect, and are affected by, mental health. The simulation was found useful in making responsible authorities in different sectors of government aware of potential partial optimization and counterintuitive behavior. Typical partial optimization in this context could be trying to save costs by a short-sighted saving in resources for proactive services, which would in due time increase the amount of expensive reactive services. Counterintuitive behavior, on the other hand, refers to decisions which have very different impact to the one intuitively intended, e.g., adding resources to reactive services with the intention of shortening the queues and waiting times can in fact increase the queues if the resources are taken from preventive services.

Moreover, simulations were considered useful for coaching the policy makers and generating an appropriate mindset for understanding the systemic interdependencies. This conceptualization is currently under validation with different levels of decision makers for further development and empirical applicability. Group model building approach is continuously used to validate the common view of the complex problem.

Important aspect of group modelling techniques is the societal embedding of joint vision and actions. The decision makers who actively participate on group modelling are committed to the system dynamic model created and they become change agents in their own organizations. Group model techniques are usually divided into model creation phase and model validation phase.

The main factor in model creation is the structural co-creation of the model. The co-creation does not require any modelling expertise from the participants, but they have a real effect on structure of the model and even parameters. The participants can easily explain the structure of the model to other people and unlike with black-box models the participant can see and understand internal phenomena.

In model validation phase the participants see how the impacts of different inputs, decisions and external disturbances propagate throughout the complex system and they can immediately pinpoint plausible and implausible phenomena as well as missing and erroneous behavior. The model is iteratively improved with the findings. Especially counterintuitive behavior (in which the impact on targeted output is not intuitive) is made understandable with validation of impact propagation in internal structures.

From network orchestration perspective, the system dynamics modelling technique connected well to the activities aiming to enhance knowledge mobility and coordination between the policy makers. In particular, it was connected to reinforcing a common identity among the network members. The discussions on potential predictive actions on mental health and unemployment problems among young people and their families especially motivated the members of the network to participate and openly share knowledge for a common agenda, and to cope with different understandings, perceptions and goals. Here, the variety of the goals and presence of non-monetary benefits became quite visible. A particular strength of SD and group model building is the focus on causal relations and what leads to the eventual outcomes. This takes a step back from “we should do this” debate that is often based on undisclosed individual anecdotal experience and easily includes territorial defense of own organization’s importance and its budget. Instead, the analysis builds a commonly discussed and accepted basis for “we should do this because of this” suggestions, that is, it increases the transparency and justification of decisions.

At policy level, there are active and enthusiastic key persons committed to this activity, and willing to orchestrate the network. They clearly recognized the potential benefits of foresight and system dynamics modelling for policy making and wanted to invest some time in building up the systemic innovation network. Many of the interviewees shared the insight of a participant indicating that “the policy makers should focus more on prevention instead of backwards problem analysis and to see the whole map (cause and consequences) and all its strategic landmarks, divide the activities among the members and then chase them to get better decisions done.” It was continued that “seeing the systemic impact of the preventive decisions would help policy makers to invest also to the actions which economic impacts will be realized in the long run”.

The importance of collecting and using the data and knowledge from different sectors (e.g. social and health sectors and from private sector) and different regions and levels was emphasized by many of the interviewees with notions like: “The information is too general level at the moment” and “With the current data we can make false conclusions.” In this context, the system dynamics modelling helped to build transparency and therefore to clarify the relations of network members between each other also in different (i.e. ministry and regional) levels.

In fact, system dynamics modelling has practices that are useful regarding such processes and routines that enable analyzing, processing, transforming, and exploiting the knowledge and information among experts in the network from different perspectives. These presentations and rapid prototyping helped policy makers to comprehend what are the relations between the different actions and indicators, and the varying views on pursued benefits were taken in consideration. It was noted in the interviews, however, that “it is important that in the system dynamic workshops the discussions will be done with actual actors and experts. The causal relationships should be based on facts, not assumptions.”

In some cases, e.g., related to the mental health and prevention services targeted to young people this might require quite deep level understanding about the domain and area of expertise. Also, it is not just the professionals that work towards the prevention of mental problems, but also those affected by this activity that need to be involved. “It is important always to listen the customer….in this case it is important to listen the young people, what services they need and what is the impact.” Therefore, the network orchestrator is placed in a challenging position, trying to identify and mobilize the relevant actors.

The challenge of the SD modelling and foresight approach also is that they are relatively complex to explain and understand without a full briefing.

The approach and working methods were introduced each time to the new participants in the workshops, as described in research design. This requires a lot from the orchestrator and designing the orchestration activities. The number of identified data sources that are relevant to mental health cause and consequences are so large and complex that it can be overwhelming for the decision makers.

Relatedly, there are many positive, preventive things happening in other sectors that may contribute to the health care also. For example, the cultural sector; sport sector and social sector, can be relevant parties to acknowledge. However, wider capture of data would be needed to see if the preventive actions made in the different sectors are important. Therefore, it is important to build tools that automatically collect the data and visualize it in the simplified manners based on the specific needs and requirements of policy makers. Considering the development of such systems, the challenge is that the data is in silos and often the current legal and ethical rules are making it difficult, even impossible, to continuously utilize data, in particular personal health and social welfare data, across the different sectors.

5. Discussion and conclusions

System dynamics modeling having its roots in control engineering and simulation analysis has been mostly applied for studying technical, mechanical, chemical, and electrical systems (Forrester 1961). This study attempts to bring the systemic view onto a complex human-social paradigm of public health which is multilayered. In addition, the studied case of preventive mental health for youth requires to look beyond the elements directly relevant to health and healthcare. As system dynamics modeling helps to build a robust understanding of a complex system, for the data-driven decision support system it is necessary to identify the data sources that can improve the robustness of the data reservoir. Through expert workshops, this study identified six (6) primary data sources and various sub-types that are relevant to the preventive mental health case. To formulate effective policies based on the developed SD model, efficient sourcing of data from each of the sources is necessary to create meaningful analysis. Towards that end, the network orchestration approach is deemed as useful that improves proper communication, creation of positive atmosphere, common agenda setting, knowledge sharing, and capability improvement (Ring & Van den Ven 1994).

According to Liotard (2017), empirical evidence from case studies show that policy makers are willing to use technological innovation to support and enhance their work. Systems thinking and systems theory are broad concepts (von Bertalanffy 1968; Weinberg 2001) and system dynamics is one view into it. Within system dynamics, what is often referred to as systems thinking comprises mainly a methodology for qualitative modelling of dynamic systems, ways to analyze and comprehend them, and help in decision-making. Out of this, specific tools can be created that improve accuracy of decision-making related to policy initiatives. Strategic decisions with long-term impacts have to be made in a rapidly changing environment with significant disruptive uncertainties taking place. Policy makers are increasingly held accountable for the impacts of their decisions. Therefore, there is a growing need for tools for visualizing the logic and complex dependencies behind the decisions, as well as for quantifying the impacts of decisions and uncertainties. System dynamic models have proven to be an invaluable aid for these demands and constantly coach decision makes into seeing the big picture and ensuring solutions for reaching the targeted impacts.

However, at the same time, it needs to be made sure that varying actors affected by the decision-making are involved. For that purpose, the principles of network orchestration can be connected with the SD modelling. The methodological innovation building on the SD logic in the context of policy making in health sector allows use of foresight and simulation methods. In our case, the research process corroborates with a number of individual methodologies: qualitative interviews, initial SD of healthcare, workshop with regional policy makers, iteration of the SD model, workshop with national level policy makers, reiteration of the SD model and create simulations, a new workshop with regional policy makers. In the process, this study combines qualitative approach (interviews and workshops) with more quantitative tools like system dynamics modelling, while doing it with along the principles of network orchestration.

During the different phases of the process, where preventive activities on mental health problems were searched for, participants brought into the discussion their personal expertise on the system in which they operate. Their input included the causal structure that they observe, stakeholders they are familiar with, and the knowledge of potentially relevant data that their (or other) organization(s) collect. While the role of network orchestrator is indistinct in this particular context, driven mostly by the research institute, in future, orchestration roles could well be formally addressed and institutionalized. Institutionalized orchestrators can then apply the methodological approaches tested here for establishing a continuous endeavor in policy making.

Intelligent, data-driven decision support systems are currently being built in many health care systems and in many countries. They are needed in order to predict the short and long term impact of the complex and multidimensional decision made by the policy makers. The foresight approach and system dynamics modelling can help policy makers and innovation orchestrators to think "big" as well as understand and communicate different data sources and complexity of cause-effects relations in policy-making situations and between the different policy-making levels and individuals. In this context, SD modelling and orchestration help ecosystem actors to create common understanding of the goals and phenomena, and thereby design such data-driven support systems that produce accurate information in timely fashion. The SD model and network orchestration are especially relevant in ensuring mobilization and knowledge mobility, coordinating and agenda setting (cf. Hurmelinna and Nätti 2017).

In our case, many of the policy makers were excited about the potential to predict future consequences of their decisions. Before this can happen, one needs to create causal model that allows us to see the potential impact of the actions from systemic perspective. The next step to this direction would be to validate the created causal relationships with the real data and to show the generated simulation tool to the policy makers who are working with the children mental health prevention. The key problem with the data based decision support tool co-creation and deployment is, however, the rules and regulations that are often denying the usage of e.g. personal data without individual consent. The laws related to the data protection and secondary data usage are however under a continuous change and it seems that the future target is to give more permissions to allow the anonymized data usage in different e.g. policy level decision support systems.

Policy making is presently comparatively reactive; to make policies that will have appropriate preventive consequences regarding mental health problems, methodological suitability is important, so that the boundary spanning characteristics are understood and explained (Sterman 2006). Using group model building of SD (Vennix 1996; Michaud 2013), this study presents the complex system of preventive healthcare with a level of abstraction that shows interconnections, causal relationships between multiple variables and stakeholders (Senge 1990; Stroh 2015). Thus, SD perspective in networked setting supports developing more data-driven tools for policy making in practice.The next step is to use the SD model to generate new decision-making processes in preventive mental health based on data and use the model to aid the actual decision-making in drafting healthcare policies. The implications are not restricted to healthcare sector alone but extend to all system level innovations.

Our study has its limitations. For instance, it can be considered as a snap shot about the use of system dynamics and certain orchestration activities, but these are just one step of the overall innovation process. On option for the future research is to look at innovation orchestration as a longitudinal activity among the policy makers and the other stakeholders. More research is needed in order to understand how the system dynamic modelling tool is used to support development of intelligent data-driven support systems in the level of the shaping health ecosystem. Furthermore, the implementation of such systems invite more attention. More conceptual research is required to identify and validate factors, services and data sources affecting on policy level decisions in the area of preventive healthcare, and beyond.

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