Opportunities for System Dynamics towards the Support of Technological Developments in Stroke Treatment Domain

Julia Kantorovich[a] and Jukka Ranta[b]
VTT Technical Research Centre of Finland, Tekniikantie 21, Espoo, Finland

Keywords: System Dynamics, Stroke Diagnosis and Treatment, Technology Developer Support.

Abstract: Data driven solutions can facilitate and enhance stroke diagnostics and at the same time management of stroke prevention and treatment in a cost-effective way. However, the potential and the utilization of data and AI analytics in stroke solutions are largely neglected. At the same time, the process to enter to medical domain for technology developer is not straightforward. There is a need for common vocabularies and design tools to engage medical professionals in interaction with technologists during the research and development phase to let them know what is needed. This paper valorises the opportunities for System Dynamics to support technology developers in the developing of innovative solutions and applications for stroke diagnosis and treatment. In addition, the value of System Dynamics to support the impact analysis (health outcome, decision quality, care costs, etc.) and hereby to facilitate the business and market uptake of new innovative solutions in this domain is demonstrated.

1 INTRODUCTION

Annually, approximately 15 million people worldwide suffer a stroke with global projections that the number of stroke survivors will rise to 77 million by 2030 (Béjot et al., 2016; WSO, 2021). Following transient ischaemic attack (TIA), at 5 years, the risk of recurrent stroke is 18.3% and at 10 years following stroke, the cumulative risk of recurrence is 39.2%, with higher death and disability noted with recurrent events. Furthermore, although 10.5% to 18.2% of patients with TIA will have a stroke within 90 days, more than 31-61% of the TIA patients are misdiagnosed (Dawson et al., 2009; Sadighi et al., 2019). Such high rates of cardiovascular morbidity and associated disability indicate the need for effective secondary prevention actions. Moreover, rapid and accurate diagnosis and treatment of stroke is important to improve health outcomes. A significant delay in treatment that may happen due to misinterpretation of stroke symptoms or inability of a person to perform necessary follow-up actions, might cause death, permanent disabilities, as well as more expensive treatment and rehabilitation.

There is a technology that has been developed to address the needs of accurate and rapid diagnosis and treatment of stroke. The examples of existing technological solutions are stroke risk calculation tools, computer-aided first stroke symptoms recognition software, remote diagnosis- and rehabilitation which is supported by telemedicine and mobile solutions (e.g. Chen et al., 2018; Bat-Orgil, 2021). However, the potential of technological solutions, data combinations and artificial intelligence (AI) to support more advanced data-driven decision support in the TIA and stroke diagnostics are not fully leveraged (Ding et al., 2020; Ali et al., 2020). Respective improvements have also a massive business potential. They can facilitate differential diagnostics, triaging, and management of cerebrovascular conditions in a cost-effective way.

The Stroke-DATA research (StrokeData, 2020) is setup to deal with these challenges and to propose a number of data-driven technological solutions to reduce the diagnostic time, to improve the outcome of the diagnosis and secondary prevention as well as to improve the satisfaction of patients and care-givers, and effectiveness of overall stroke treatment processes (see Figure 1).

[a] https://orcid.org/0000-0001-7598-6175
[b] https://orcid.org/0000-0002-1376-542X

Kantorovich, J. and Ranta, J.
Opportunities for System Dynamics towards the Support of Technological Developments in Stroke Treatment Domain.
DOI: 10.5220/0010983700003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 743-750
ISBN: 978-989-758-552-4; ISSN: 2184-4305

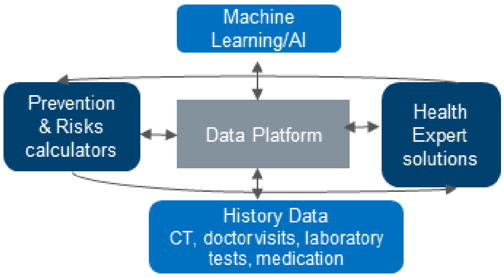

Figure 1: Envisioned Stoke-DATA solutions.

However the experience gained during the first six months of the project had revealed that this task is far from straightforward. It can be cumbersome for technology developers to grasp the complex domain of TIA- and stroke treatment, to master the needs and to find a respective niche towards the technological development and business success. Moreover, it is also not an easy task to engage medical professionals into discussion on needs, to demonstrate the ability of technology, and to prove the impact value of the proposed solution to various stakeholders involved in the stroke care processes.

System Dynamics and Systems Thinking models have potential to connect various stakeholders and to provide technology developers with means to grasp the complexity of stroke domain. System Dynamics is based on Systems Thinking and Group Model Building principles. Systems Thinking helps to learn the definitive characteristics of the systems, how systems fit in a larger context of day-to-today life, how they behave and how to manage them (Sterman, 2000). Group Model Building has been found to be a useful method for engaging different stakeholders to both elicit their perspectives to address difficult and complex problems and share those perspectives and expertise (Richardson, 2007).

Consequently, the objective and the first contribution of this research is to valorise the opportunities for System Dynamics towards the supporting of technology developers in the developing of innovative solutions (applications) for stroke diagnosis and treatment. The second contribution of this research is to demonstrate a value of System Dynamics to support the impact analysis (health outcome, decision quality, care costs, etc.) and hereby to facilitate the business and market uptake of new innovative solutions in this domain.

This paper is organised as follows. Chapter 2 gives an introduction to the stroke domain and its respective challenges and possibilities for the technology development. The background related to the System Dynamics modelling and its application to stroke treatment are presented in chapter 3. The identified opportunities and needs for System Dynamics are also discussed there. The first modelling efforts are presented to support the respective discussion in Chapter 4. Chapter 5 concludes the paper, outlining also the aspects of next steps of research.

2 STROKE AND TECHNOLOGY

A stroke is a medical condition in which poor blood flow to the brain causes cell death. There are two main types of stroke: ischemic, due to lack of blood flow, and haemorrhagic, due to bleeding. Both cause parts of the brain to stop functioning properly. Signs and symptoms of a stroke may include an inability to move or feel on one side of the body, problems understanding or speaking, dizziness, or loss of vision to one side. Signs and symptoms often appear soon after the stroke has occurred. If symptoms last less than one or two hours, the stroke is a transient ischemic attack (TIA), also called a mini-stroke (Donnan, 2008).

Early recognition of stroke is deemed important as this can expedite diagnostic tests and treatments and thus reduce the severity of damage. In fact, more rapid and accurate diagnosis and early preventive treatment, “the 90-day stroke risk” can be decreased by 80% after the TIA episode. Accordingly all attempt and means are needed to decrease the time from symptom onset to acute stroke treatment.

Advanced age is the most important however unmodifiable risk factor for stroke, as stroke rates double for every 10 years of age after the age of 55. The INTERSTROKE study performed in 22 countries identified 5 risk factors which together accounted for 80% of the population-attributable-risk for stroke, namely hypertension, current smoking, abdominal obesity, poor diet, and lack of physical activity (O'Donnell et al. 2010).

Furthermore, organization of stroke treatment and care has advanced beyond stroke units and in-hospital phase, and it includes multiple overlapping processes including primary prevention, emergency medical systems, acute care and rehabilitation, secondary prevention to avert stroke recurrence and long-term follow-up supported by public education, community campaigns, and research.

Technology can potentially support and enhance health outcomes in all treatment stages, we call them stroke ‘care path’ stages. For example, in case of incident of stroke, the sooner a diagnosis is made, the earlier the treatment can begin and the better the expected outcome is for the patients. An MRI scan is very useful in detecting ischemic stroke, however it is usually not available in pre-hospital phase (emergency room, home) due to its cost. Clinical tests like the Face Arm Speech Test (FAST) are helpful tools used by neurologists and trained nurses, but there may not be professional help immediately available to conduct the tests.

The computer-aided stroke presence assessment over facial motion weaknesses and speech inability for patients with suspicion of stroke showing facial paralysis and speech disorders in an acute setting using for example camera and speech recognition software on mobile phone is one example of technology proposed by researchers (Khriyenko, et al., 2018; Yu et. al, 2020). Other examples are the computerized decision support tools, which are based on risk scoring and may provide access to expert advice, improve GPs' diagnostic accuracy (in primary care setting), limit emergency department referrals of high-risk patients and prompt GPs to initiate secondary prevention in case of specialist consultation is anticipated to be delayed. Furthermore, numerous smartphone apps are available that can assist with stroke rehabilitation and recovery process.

Artificial neural networks are a powerful AI tool for automatic diagnostics of diseases and has a potential in decision-making support. Machine learning and compute vision have been applied in clinical informatics and have shown commercial potential in symptom detection and classification (Wang & Luo, 2016).

Finally, large databases of patient data are being captured in hospitals which, if accessed, provide a wealth of information about disease treatment and prevention. Handling data sets and analysis of data have become a major growth area of interest globally (Marshall, 2016). Mobile medical technology is expanding with multiple diagnostic and monitoring platforms using mobile app systems which can require new ways of approaching to data analytics.

Overall, it was predicted that technologies such as telehealth, eHealth, big data and AI would have significant 30-50% impact on the improved mortality rates in acute care cases by 2025 (Polycom, 2015).

Last but not least, data platform economy has emerged (Baltimore, et al., 2016). There are many players such as Amazon, Google, Uber that are making business and creating value with platforms. Platform economy is based on data, components, algorithms and applications that are creating an infrastructure in which the platform-based markets and ecosystems operate. However, this approach is not yet fully utilized in the fragmented and highly regulated healthcare market. In order to be successful in the business perspective, the technology providers should either build platform solutions that are complementary between each other, or platform solutions that are complementary between the stakeholder players in their target market.

However, the process to enter to medical domain of stroke treatment for technology developer is not straightforward. There is a need for common vocabularies and design tools to engage medical professional in interaction with technologists during the research and development phase and to let them know what's needed.

System Dynamics is a perspective and a set of conceptual tools that have been used decades to study the structure and dynamics of complex systems such urban and industrial systems (Forrester, 1961, 1969). Later, System Dynamics has been also leveraged in other fields including healthcare domain to support to master the complex health processes, to plan actions and to affect the respective domain policies. However, its value to support technology developer is not yet exploited widely. The related existing research and the opportunities for System Dynamics are further discussed in the following (Section 3).

3 SYSTEM DYNAMICS

System Dynamics is a Systems Thinking based approach for examining how certain things in the real world change over time. The system's internal structure, which is represented by system components and the cause-and-effect connections among them, determines the dynamic behaviour of the system and how it responds to changes (Sterman 2000).

The causal loop diagrams and stock-and-flow diagrams are used in system dynamics to capture the interactions between components. Causal loop diagrams consist of variables connected by arrows denoting the causal influences among the variables and the feedback loops, chains of causal links that balance or reinforce on themselves, in the system.

Stock-and-flow diagrams highlight the accumulation and flow of information, materials, financial assets and people in and between the components, respectively.

Overall, modelling is an iterative process of scope selection, hypothesis generation, causal diagramming, quantification, and reliability testing. Qualitative models can be used to discuss and to promote structural insights and the behaviours of the system, thus, quantitative simulations allow users to see how different choices (selected parameters) lead to different plausible futures. The models are powerful tools for communicating across sectors and for motivating stakeholders to work together to make systemic changes in their systems. Furthermore, System Dynamics models can be used to tackle 'data-poor' problems. The information base for the conceptualisation and formulation of System Dynamics models can be based on experts' opinion and they can be also broader than the numerical database applied in operations research and statistical modelling. Group Model Building (GMB) is a tool to acquire expert knowledge and to identify modelling needs. Group Mode Building refers to a system dynamics model building process in which the stakeholders are actively involved in the process of model construction that explore questions such as: what is exactly the problem faced? How did the problem situation originate? What are the underlying causes? (Rouwette, et. al., 2020). On the other hand, system dynamics can become very complex when real world situations with lots of variables are modelled. Some issues that may rise are related to the data availability, domain understanding, and modelling systems' boundaries and uncertainties.

The System Dynamics modelling was actively used in healthcare research to address a range of issues (Davahli et al., 2020; Darabi et al., 2020), such as organizing healthy community programs and policy initiatives, improving processes and costs of primary and acute healthcare as well as health equality, developing new approaches for chronic disease prevention and control, addressing the disease epidemiology including work in heart disease, diabetes, HIV/AIDS, cervical cancer and other diseases. However, the existing effort is very much dedicated to the medical side of the problem and towards the enhancement of outcome and quality of healthcare systems' processes. The value of systematic thinking and system dynamics to support technology developers is not yet exploited. Therefore, the aim of this study is to address this gap by valorising the opportunities for System Dynamics to support the development of new data driven solutions in stroke treatment domain, more specifically:

- How System Dynamics modelling can support technology developers in the process of designing new innovative solutions in the domain of stroke diagnostics and treatment.
- How System Dynamics modelling can engage medical professionals in interaction with technology developers to acquire the needs.
- How System Dynamics approach can support technology developers in successfully taking their product to the market and the decision makers in the process of planning for the procurement of a new technology.

4 DEVELOPER SUPPORT

As discussed earlier, data driven approaches can potentially facilitate and enhance differential diagnostics, triaging and at the same time management of stroke prevention and treatment in a cost-effective way. However, the potential of the mobile solutions and in particular utilization of data combinations in the TIA and stroke risk evaluation and diagnostics are largely neglected. At the same time, possible efficient use of the available data, via artificial intelligence, in the form of more advanced, data-driven decision support systems is not yet under development.

Accordingly, the focus of our first modelling efforts has been put on improving our understanding about the role of data in the stroke treatment domain. We started with domain analysis (facilitated by literature review and interviewing experts), consequently the initial models have been created to valorise the role of the data in various stages of stroke treatment and care path. At the next step, the Group Model Building (GMB) Workshop has been organised to connect medical experts and technologists and to collect medical experts'- and technologists' opinions on first models towards their adjustment. The aim of GMB was to facilitate the discussion and obtain more insights on the aspects related to 1) what overarching data based stroke treatment tools could be and 2) what is needed for a data driven tools to become a successful product.

On the first point, more specifically:

What is the valid data to be used in TIA & stroke diagnostics? What data need to be collected for TIA & stroke service development? What data sources can be used? What kind of solution and data combination would work for TIA & stroke prevention? What is the required quality of data to support the development of algorithms to be used in effective stroke diagnostics? How data is related to stroke 'care and treatment quality' and 'health outcome'?

On the second market uptake point, more specifically:

What is needed for a data tool to become a successful product and what stakeholders are needed and what kind of ecosystems are to be created? What will facilitate the adoption of developed solutions by end users? How shall we orchestrate the connected health ecosystem for the solution, so that it supports the strategies and creates value for patients, hospitals and technology providers?

The modelling effort and workshop discussions have led us to the initial definition of two models "Data flow" and "Market Uptake" models, which are discussed in the following.

4.1 Stroke-DATA Models

The model to facilitate planning of data driven decision tools is presented in Figure 2. As a conceptual framework it aims to structure discussions on the relation between existing data, opportunities for technological solutions, and the eventual value of a tool. It gives an overview of three distinct layers, listing from top to bottom: historical data available for development, features and functionalities of the tool, care pathway and impact of using the tool. Different experts tend to have a strong focus on their own topic. This model and respective discussions helped them to see there interdependencies and construct an overview while discussion potential tools.

The top part summarizes the types of existing data that can support the design of the tool, in particular developing the analytics and the underlying technological infrastructure. Considering a hypothetical tool, the detailing of the data both places constraints on the analytics that can be implemented while design of the tool defines which of the existing data should be acquired. Focus should not be limited to constraints imposed by the data but also include exploration of opportunities in discussion between the experts, i.e. not only prune out ideas presented by the technology experts. Actual access to the data and also level of available detail are of concern as data security and privacy protection limit how and for what purposes these data may be used.

Below the data cloud are the specific use cases, analytics, and functionalities that can provide added value in the stroke care pathway. A key consideration here is to bridge the gap between what the available data can support and what generates added value when implemented in the care pathway. This is mainly the domain of expertise of the technology developers.

The bottom part visualizes the influence of data availability during care, impact on care quality, and eventually on health outcomes. The causal effects run down, from available data to care quality to health outcome, and to the right, from one care stage to the next. We are considering a tool based on using data and analytics to support care both in each stage and to integrate the care across stage. The purpose of the tool

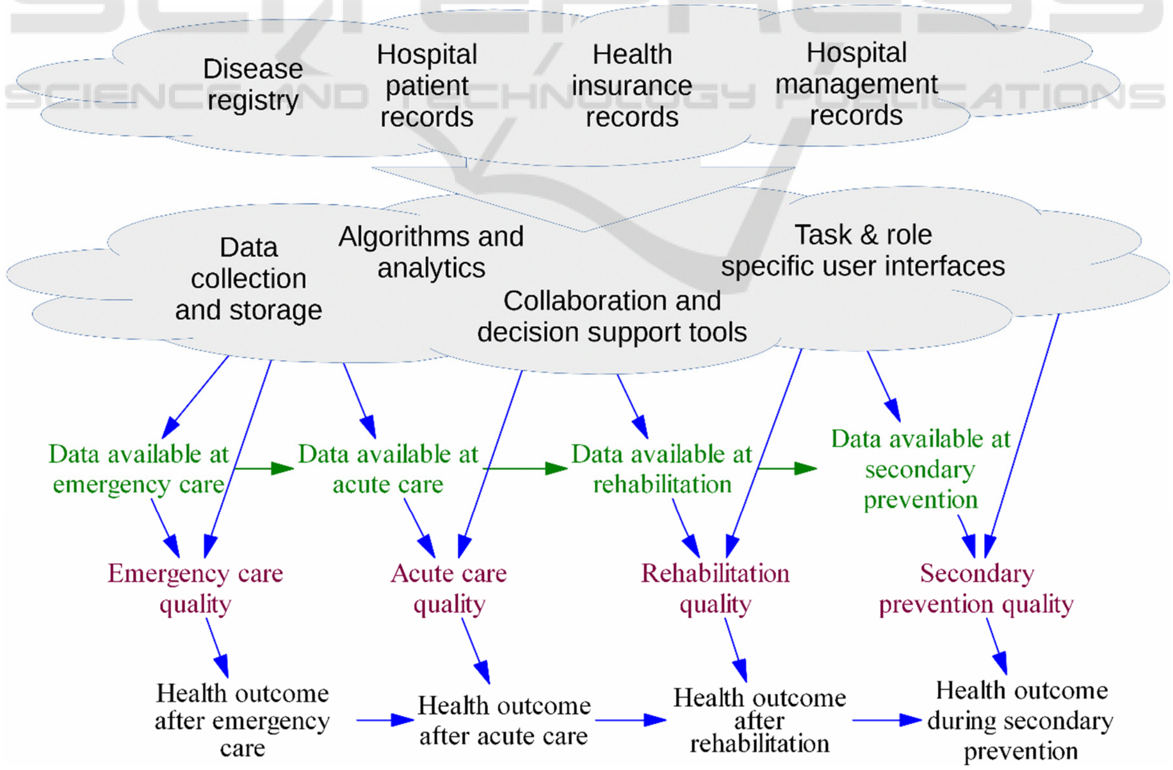

Figure 2: Conceptual model of factors and their dependencies from available data and eventual impact on health outcomes.

is to facilitate better data availability from patient records, reflect these to research data via the analytics and thus improve care quality and outcomes.

The availability of data is dependent on both linking to various currently used records and also to similar tools used in previous stages of care, i.e. recording data and making it available in later stages of care supports a better basis for decision making. Such transfer of data involves crossing boundaries between units and wards within a hospital and also across organizational boundaries. Health outcomes are dependent on both previous outcomes and quality of care in the current stage of care. In particular, failure to provide appropriate care in earlier stages can lead to irreparable damage and disability.

The different stages of care had their own focused discussions in a workshop. More focused diagrams, such as the one presented in Figure 3, were used. Only one stage of care is included here, the data and app feature are compacted, and the orange colour indicates the desired focus of discussions. As an example, we present here a summary of the results from discussion on emergency care. Of the tools and devices, it was noted that they should add as little as possible to existing equipment in ambulances and overall the simplicity of use and streamlining into current protocol was considered crucial for success.

In particular, value was seen in the seamless integration to existing systems both in ambulance and hospital emergency department, and further, linking the care stages by allowing early information to doctors in hospital prior to patient's arrival and possibility of ambulance crew to consult specialists in hospital.

Also, value was seen in analytics providing more reliability in differentiating between stroke vs. TIA vs. other condition and in case it is a stroke, clot vs. bleeding - in particular when they would reduce the needed measurements and imaging and the time to make decisions.

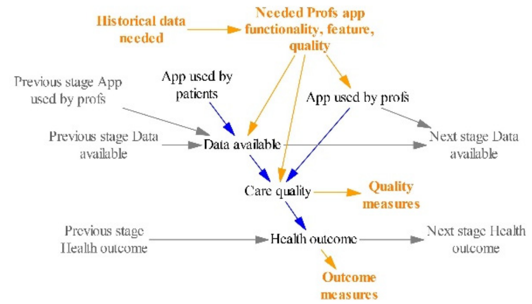

Figure 3: Model for a single stage in the care-path used during workshop discussions.

Other areas of potential utility were considered in helping with triage with awareness of current hospital resource constraints and linking to the patient's historical medical records (especially history of TIA or stroke). Of outcome measures, mortality and Cerebral Performance Categories Scale were mentioned but the topic appeared to be difficult to bring into discussion while discussing hypothetical data tool properties. This possibly is a topic that only surfaces once there is a more concrete plan of a tool or the tool already exists, i.e. the value proposition on

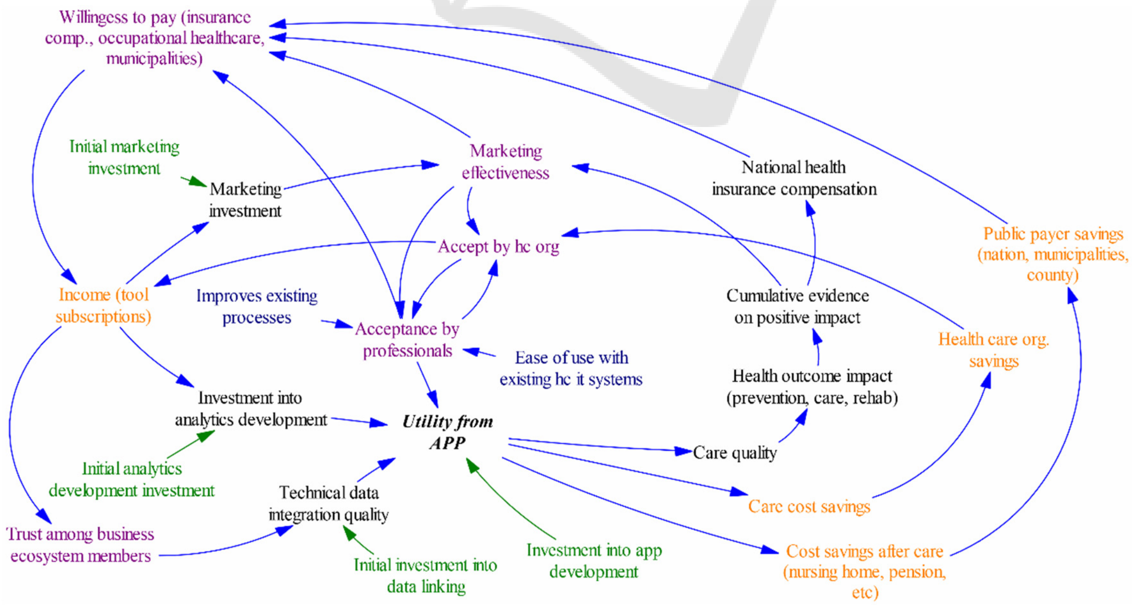

Figure 4: Model of market update dynamics.

that level is something of an afterthought. The more direct effects a data tool could have on care were more easily covered in the discussions. Timeliness and correctness of different decisions were brought up along with possibility of reacting to weaker indications before severe symptoms develop.

The market uptake model in Figure 4 is in the format commonly used in Systems Thinking and depicts a dynamic causal diagram with factors and actors that can influence whether the tool is eventually widely used and profitable for the members of the business ecosystem. The causal directional dependencies are represented using arrows. Colouring of some of the variables indicates grouping into monetary factors (orange), opinions and perceptions (magenta), and initial investments (green).

At the core is the *Utility from APP*, which represents the various benefits (and drawbacks) resulting from using the app (and its data backend functionality) as a part of the care processes along the care pathway. The benefits are dependent, first of all, on the tool being used (*Acceptance by professionals*) and then on integrating data (*Technical data integration quality;* both historical research data and case specific patient data) and developing analytics that serve as basis for decision support functionality (*Investment into analytics development*).

Using the app leads to savings in the active care stage and later life and also to improved quality of care and thereby health outcomes. Evidence of improved quality of care and health outcomes accumulates over time and can lead to positive compensation decision by the national health insurance and also more effective marketing to various healthcare organizations. Though dropped from the visualization, it was noted in the workshop that such accumulation of evidence is enhanced by co-operation also with researchers.

Implementing the app in the healthcare processes is dependent on both organizations accepting it (*Accept by hc* org) and individual professionals accepting it (*Acceptance by professionals*), i.e. it is made available by the organization and the employees actually use it. As the doctors are respected experts in their field and often also participate in management, they have much say in the decisions of the organizations. Therefore, there is the interplay, arrows in both directions, of acceptance by healthcare organization and the professionals. There was a comment in the workshop that this interplay can vary between organizations and also over time, which should be taken into account when planning marketing activities. Further, the degree to which professional uses the app depends on how it fits into existing routines, i.e. *Ease of use with existing hc it systems* and *Improves existing processes*.

Income from licences and subscriptions allow further investments into developing the tools, which helps to better meet user needs and improving outcomes. The income also allows further investments into marketing, thus widening the user base. Also, positive and profitable experiences of cooperation between the business ecosystem leads to greater *Trust among business ecosystem members*. This allows arrangements to open more of the IPR to the members, thus improving the interaction between components of the app.

5 CONCLUSIONS

This paper has presented the initial System Dynamics models to support technology developers in entering the complex domain of stroke diagnosis and treatment. The modelling work has been supported by the Group Model Building activities, where the medical experts, technology developers and researchers met to provide expertise and to share open issues, challenges and opportunities for the technology development in the stroke treatment domain. During the workshop it was acknowledged that the resulted models and the respective discussions can service various stakeholders in grasping the emerging important role of data and its impact on stroke care quality and health outcomes as well as what makes data tool to become a successful product and what kind of ecosystems need to be created to facilitate market uptake.

The level of details presentable in a system model is coarse with regards to individual variables of the model. They essentially are constrained to a few words. On the other hand, a large number of variables, i.e. detail on how many different things the model tries to account for, results in a model unusable in a workshop as the overall big picture is lost. In the authors' experience, presenting a preliminary model based on e.g. interviews helps start the discussion as it provides something to criticize and expand upon. However, such initial models need to be sufficiently simple to be understood after a short presentation.

As for the future work, a set of quantitative simulations will be developed to support the examination of care quality outcomes in various stages of stroke treatment care path. Moreover, the market uptake model will be quantitatively instantiated to study the dependences between the initial technological investments and various impacts such as care quality and cost savings.

The modelling and workshop with the ecosystem members aimed to focus and strengthen the ecosystem. It was brought up in the workshop that, though the current activities of the ecosystem focus on the stroke and a specific type of tools, longer time horizon objectives can cover also other diseases and tools. Thus the market uptake model could be expanded or restructured to account for development of new, as of yet unspecified, tools and applications. For example, going from an uptake model to ecosystem evolution model the specific "app" in the model could be replaced by an evolving portfolio of offerings from the ecosystem and the definitions of other components of the model would need to be redefined accordingly.

ACKNOWLEDGEMENTS

This research was funded by Business Finland under Stroke-DATA project

REFERENCES

Ali, F., Hamid, U., Zaidat, O., Bhatti, D., & Kalia, J. S., 2020. Role of Artificial Intelligence in TeleStroke: An Overview. Frontiers in neurology, 11, 559322. https://doi.org/10.3389/fneur.2020.559322.

Baltimore, D. R. Charo, Kevles, J.D. Benjamin, R., 2016. The Rise of the Platform Economy, Issues in science and technology. Online, issues.org.

Bat-Orgil B.E & Jeffrey L., 2021. Automatic Acute Stroke Symptom Detection and Emergency Medical Systems Alerting by Mobile Health Technologies: A Review, Journal of Stroke and Cerebrovascular Diseases, 30 (7) 105826.

Béjot Y, Daubail B, Giroud M., 2016. Epidemiology of stroke and transient ischemic attacks: Current knowledge and perspectives. Rev Neurol (Paris). 172(1):59-68. PMID: 26718592.

Chen Y, Abel KT, Janecek JT, Chen Y, Zheng K, Cramer SC., 2018. Home-based technologies for stroke rehabilitation: A systematic review. Int J Med Inform. 123, 11-22.

Darabi, N., et al., 2020. System Dynamics Modeling in Health and Medicine: A Systematic Literature Review. Syst. Dyn. Rev.. doi: 10.1002/sdr.1646

Davahli, MR., et al., 2020. A System Dynamics Simulation Applied to Healthcare: A Systematic Review. Int J Environ Res Public Health, 17 (16), 5741.

Dawson J, et al., 2009. A recognition tool for transient ischaemic attack. QJM, 102, 43-49.

Ding L, et al., 2020. Incorporating Artificial Intelligence Into Stroke Care and Research, Stroke AHA, 15 (12), 351-354.

Donnan GA, Fisher M, Macleod M, Davis SM., 2008. Stroke. The Lancet. 371 (9624), 1612–23.

Forrester, J.W., 1961. *The book,* Industrial Dynamics. Cambridge, MA: The MIT Press. Reprinted by Pegasus Communications, Waltham, MA.

Forrester, J.W., 1969. *The book,* Urban Dynamics. Cambridge, MA: The MIT Press. Reprinted by Pegasus Communications, Waltham, MA.

Khriyenko, O., Rönkkö, K., Tsybulko, V., Piik, K., Le, D. P. M., & Riipinen, T., 2018. Stroke Cognitive Medical Assistant (StrokeCMA). GSTF Journal on Computing, 6 (1). doi: 10.5176/2251-3043_6.1.112

Marshall DA, Burgos-Liz L, Pasupathy KS, Padula WV, Ijzerman MJ, Wong PK, et al., 2016. Transforming healthcare delivery: integrating dynamic simulation modelling and big data in health economics and outcomes research. Pharmacoeconomics. 34, 115–1126. doi: 10.1007/s40273-015-0330-7

O'Donnell MJ et al., 2010. INTERSTROKE investigators. Risk factors for ischaemic and intracerebral haemorrhagic stroke in 22 countries: a case-control study. Lancet. 376 (9735):112-123.

Polycom, 2015. Healthcare in 2025 2025 Healthcare Technology Innovation Survey, Online by Polycom.

Richardson, G.P., Vennix J., Andersen, D.F., Rouwette E., 2007. Group model building: problem structuring, policy simulation, and decision support. Journal of Operational Research Society, 58, 691–694.

Rouwette E.A.J.A., Vennix J.A.M., 2020. *The book,* Group Model Building. In: Dangerfield B. (eds) System Dynamics. Encyclopedia of Complexity and Systems Science Series. Springer, New York, NY.

Sadighi, A., Stanciu, A., Banciu, M., Abedi, V., Andary, N. E., Holland, N., & Zand, R., 2019. Rate and associated factors of transient ischemic attack misdiagnosis. eNeurologicalSci, 15, 100193.

Sterman J., 2000. *The book,* Business dynamics. Systems thinking and modelling for a complex world. McGraw-Hill.

StrokeData, 2021. The Stroke Data Research, https://www.strokedataproject.com/.

Yu M. et al., 2020. Toward Rapid Stroke Diagnosis with Multimodal Deep Learning. In: Martel A.L. et al. (eds) Medical Image Computing and Computer Assisted Intervention – MICCAI 2020. Lecture Notes in Computer Science, vol 12263. Springer, Cham. https://doi.org/10.1007/978-3-030-59716-0_59

Wang K, Luo J., 2016. Detecting Visually Observable Disease Symptoms from Faces. EURASIP J Bioinform Syst Biol. 1 (13), doi: 10.1186/s13637-016-0048-7. PMID: 27688744; PMCID: PMC5007273.

WSO, 2021. World Stroke Organization facts. https://www.world-stroke.org/world-stroke-day-campaign/why-stroke-matters/learn-about-stroke