

SPATIAL PSYCHIATRIC HOSPITALIZATION MODELLING IN AN INTERNATIONAL SETTING – AN AGENT BASED APPROACH

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ABSTRACT

Modeling and simulation in international health care resource planning and future strategy testing has growing impact and importance. Within the CEPHOS-Link FP7 project a dynamic agent-based model is integrated for Austria, Slovenia and the Veneto region of Italy for answering questions defined in PICO structure for psychiatric disease hospitalization and re-hospitalization under special constraints using big national claims databases combined by using a well-defined data pooling process. The basis for the dynamic simulation process is a generic population concept (GEPOC) developed within the DEXHELPP consortia project in Austria and parameterized and calibrated using EUROSTAT and national statistics databases. Regional concepts are simulated based on NUTS-3 distance of service information integrated by driving time calculations. All results are gathered on a personal level and depicted and described on age gender groups added by cost-information.

Keywords: health care simulation, agent-based model, spatial dynamics, international claims data

1. INTRODUCTION

High re-hospitalization rates are often regarded as an indicator of malfunctioning of hospitals and health care systems. This applies especially to mental health care where the term “revolving door psychiatry” has been coined for this situation. However, when evaluating mental health care systems, international comparisons of psychiatric re-hospitalization rates derived from routinely collected health care data are hampered by different ways of establishing them in different countries with different health care systems and different data collection routines, and cannot be used at face value.

1.1. General objective

The overall objective of the CEPHOS-LINK project was to compare with a common study protocol psychiatric re-hospitalization rates in six European countries (Austria,

Finland, Italy/Veneto, Norway, Romania, and Slovenia) for adult patients, and to identify predictors by regression analyses in a retrospective cohort study design, first locally for each country dataset and then centrally with a pooled dataset. A crucial innovative aspect and challenge of this project was that observational data from large national electronic health care registries in six different countries with different care systems and different data collection routines were used. The major advantage of this approach is that very large unselected patient populations can be applied to all countries thereby reducing the “methodological noise” inherent in systematic reviews of separate studies.

The CEPHOS –LINK patient dataset for the pooled analysis consists of finally 225.600 patients fulfilling the inclusion criteria. Besides the development of a data pooling protocol.

1.2. The modelling objective

Besides classical statistical analysis (logistic regression and Cox- regression models) questions regarding long time behavior and planning of resources arise. As identified by systematic literature research dynamic modelling methods are up to now underrepresented in the solution of re-hospitalization research (Urach, Zauner, Wahlbeck, Haaramo and Popper 2016) These demand is iteratively formulated within three research questions defined based on concepts used in health technology assessment (HTA) and evidence based medicine (EBM) called PICO, especially influenced by Aslam and Emmanuel (Aslam, Emmanuel 2010). Within this concept the population, innovation comparator and outcomes are defined. In short these are:

- Task A: How will first hospitalizations and re-hospitalizations change in the future due to demographic change?

- Task B: How does theoretical improvement of the care structure in certain NUTS-3 regions impact re-hospitalization rates?
- Task C: What is the possible impact of rising diabetes prevalence on psychiatric re-hospitalizations?

Task B is based on findings of the Italian research partner within CEPHOS-Link (Donisi, Tadeschi, Wahlbeck, Haaramo and Amaddeo 2016). Task C is based on results from descriptive claims data analysis and literature research (Sprah, Dernovsek, Wahlbeck and Haaramo, 2017). In all tasks the entire populations are adult patients (+18 years old), tasks A-C describe the innovation. The comparator is the actual situation out of the claims data (Breitenecker et al. 2011) and the outcomes of interest are the number of hospitalizations/re-hospitalizations per year, gender, diagnosis group and age group. As well as the total costs – to get comparable results the purchasing power parity (ppp) cost data sets are implemented.

1.3. Statistical analyses

Each country identified adult patients (18+ years old), discharged for the first time over a period of 12 months from a psychiatric inpatient bed with a primary functional psychiatric diagnosis (ICD-10 F2-F6). These patients were then followed up over one year. One major restriction was that there was no censoring for death during follow-up included in the analyses.

Local single level logistic and Cox regression were performed in order to identify predictors for psychiatric re-hospitalization, as well as for re-hospitalization to any hospital. To guarantee comparable results and techniques the patient cohort was defined iteratively with a stepwise quality assessment lead by IMEHPS Research.

The predictor variables used in the logistic regressions where the gender, the age of the patients as a dichotomous variable based on the age distribution in the six partner countries, the classification of the disease (F2 or F30 or F31 vs. the other F3 diagnoses up to F6) and the length of stay of the index hospitalization. In a further step physical comorbidities identified by the additional diagnoses at the index hospitalizations are taken into as additional predictor.

Multilevel logistic regression analyses were performed with additional contextual/geographical variables on the NUTS3 level of a patient's place of residence (degree of urbanity, Gross Domestic Product).

For countries having a broader data set on linked data on single person level also outpatient contacts of the patients after discharge – Austria, Slovenia and the Veneto region of Italy - from the index hospitalizations, analyses for the three potential extramural care events:

- Ambulatory care (a patient visits a psychiatric doctor/a psychiatric service and gets treatment/advice/ therapy for a short time period - usually less than one hour – and leaves again)
- Day care (patients visit a psychiatric day care unit for several hours and participate in a structured therapeutic program)
- Mobile service (a psychiatrist/psychiatric care team visits a patient at home/or similar environment)

are realized using the time line information of the extramural events and firstly analyzing for any event. In the last step the logistic regressions are split up for the three types of contacts and influence of outpatient contacts and re-hospitalization under the given predictive parameters has been discussed.

2. GENERAL POPULATION MODEL

As the patient always poses the center of interest, valid prognostic modelling for decision support in the health care system is only possible if the underlying population is predicted validly as well. Doubtlessly long-term epidemiological or health-technology-assessment models can never be valid if the underlying population growth or decay is not considered. This becomes clear thinking about an average chance of about one percent that an Austrian inhabitant leaves the country or dies during one year. Hence, on the average, every 100th person is “replaced” by an immigrant or newborn child every year leading to a highly fluctuating population.

Moreover a valid population model is not only a necessary part of any model in health-care science; it is also a reusable basis model for different applications.

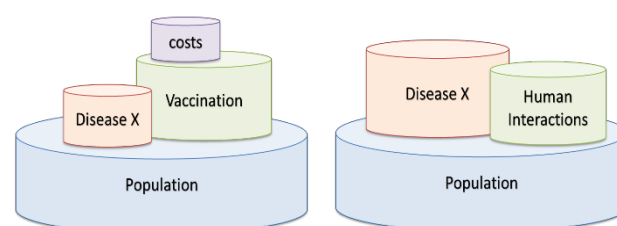


Figure 1: Left: Cost-Effectiveness model for disease X based on a population model. Right: Epidemics model for infectious disease X based on a population model.

2.1. GEPOC - Population Model

Although the Generic-Population-Concept (GEPOC) originally does not pose for a model, but for a generic modelling concept summarized in a broad handbook, the main result of the GEPOC project was achieved by a versatile agent-based model to simulate population of Austria until 2050 (starting in 2006). Hence we will moreover identify this model by the name of the project.

The agent-based modelling techniques is generally applicable for dynamic modelling and simulation of the underlying tasks A, B and C as the focus lies on populations with spatial constraints like restrictions regarding care and the social status, as well as heterogeneous patient characteristics. In the literature agent-based modelling in the hospital care setting is more often used for local in-house simulation especially in hospital wards (Taboada, Cabrera, Epelde, Iglesias, Luque 2013) but there are also new papers in the field of combined effects modelling (Silverman, Hanrahan, Bharathy, Gordon, Johnson, 2015; Kalton, Falconer, Docherty, Alevras, Brann, Johnson, 2016). Generally often economic effects on heterogeneous patient care is under discussion. For such problems, agent-based techniques seems to be the method to choose.

As Austria's population consists of individuals, they are represented by agents (or individual-agents) in the model. As it might not be possible to simulate millions of agents at once, finally one model agent stands for a hole aggregate of people (e.g. 10 or 100 henceforth denoted as K) which all behave alike.

As model borders do not take into account to simulate immigrants before they immigrated, a second type of agent needs to be introduced: the government-agent. This type of agent is responsible for the creation of newly immigrated individual-agents (Bicher et al. 2015, Bicher and Popper 2016).

2.2. Parameterization

While the available data is given on the aggregate level it is main task of the parameterization process to calculate parameter-values for the individual level – i.e. probabilities that hold for **one representative** person = agent for one model time-step.

While total numbers for a specific point in time (like total number of Austrian inhabitants at 2003.01.01) can be processed quite easily, classically by simple divisions – e.g.

$$P(\text{agent's sex} = \text{female}) = \frac{|\text{number of female persons in Austria}|}{|\text{number of total persons in Austria}|},$$

it is a little bit more difficult to process “differential-numbers”, i.e. numbers that are valid for a specific time-span (like total number of immigrants, emigrants,... during a year), to probabilities that are valid for one specific time-step as the length of the time-step is arbitrary.

Representative for all other “differential” parameters we show the parameter calculation process on the example of the death-probability. Given the number

$$X: = \text{“average yearly deaths of 100000 Austrians during year= } y \text{ for age=a and sex=s”}$$

The corresponding parameter value $Pd(t, \delta, a, s)$ (days as unit for δ) can be approximated by

$$Pd(t, \delta, a, s) = 1 - \left(1 - \frac{X}{10000}\right)^{\frac{\delta}{365}},$$

which is valid for all $t \in [y, y + 1)$. This formula can be attributed to the geometric distribution.

The model was implemented in Python 3 and (usually) executed with CPython 3.3. Attempts to execute the model with the faster Python like Pypy 3.3 unfortunately failed due to incompatibilities with the python numeric package NumPy.

The source-code is structured into four different classes: The simulation-class is responsible for the initialization and the dynamics of the model. It creates and addresses instances of the agent-class and additionally takes on the role of the government-agent. It furthermore creates and controls an instance of the protocol-class and the sampler-class. Each instance of the agent-class poses for one individual-agent and hence represents K persons in reality. The protocol-class is responsible to save all necessary data of the simulation run. The sampler-class is responsible for the parameterization of the data-driven background of the model. We do not want to go into detail about the specific classes.

2.3. Model Validation

Validation of a model denotes the process wherein the model respectively the model results are finally compared to reality. This is necessary in order to finally state the claim: The model is *valid* and can be used to predict reliable prognosis, or the model is *invalid* and needs to be re-conceptualized. In reality the result of this process is usually neither black or white, but much more a set of nuances on a grey-scale stating which parts of the model produce rather valid results and which parts need to be treated carefully as errors might be involved. It is a general fact that, as we cannot look into the future, no predictive model can be said to be perfectly valid.

As the data required to parameterize the model was also gained from Statistics Austria, this process directly compares the modelling method with the statistical regression-method. The connection of the claimed Statistics Austria data to both models is visualized in Figure 2.

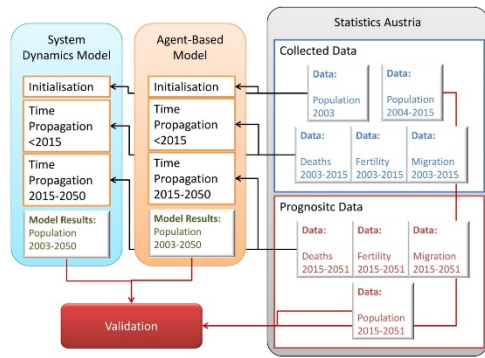


Figure 2: Summary of the connection between Statistics Austria and the two GEPOC models, the agent-based model and the system-dynamics model. Black arrows indicate the usage of data for parameterization. Red arrows indicate usage and comparison of data during the validation process.

The validation process was very successful. We compared the agent-based model (mainly) with $\delta = 365 \text{ days}$ and $\delta = 30 \text{ days}$ with data collected from Statistics Austria planning to show that the model delivers valid results for different step-sizes. Some chosen results of this process can be seen in Figures 3-4

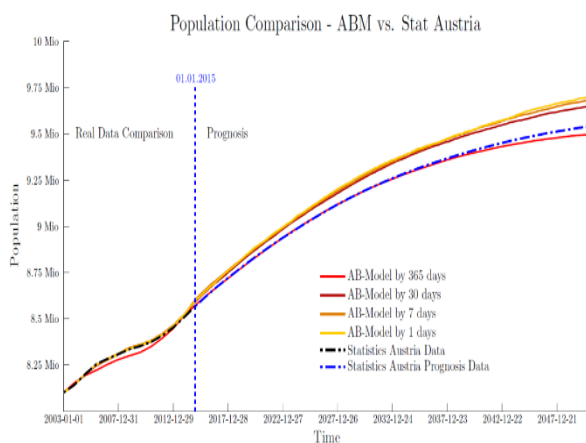


Figure 3: Temporal development of the total population. Results of simulation with different model time-steps compared with Statistics Austria data/prognosis.

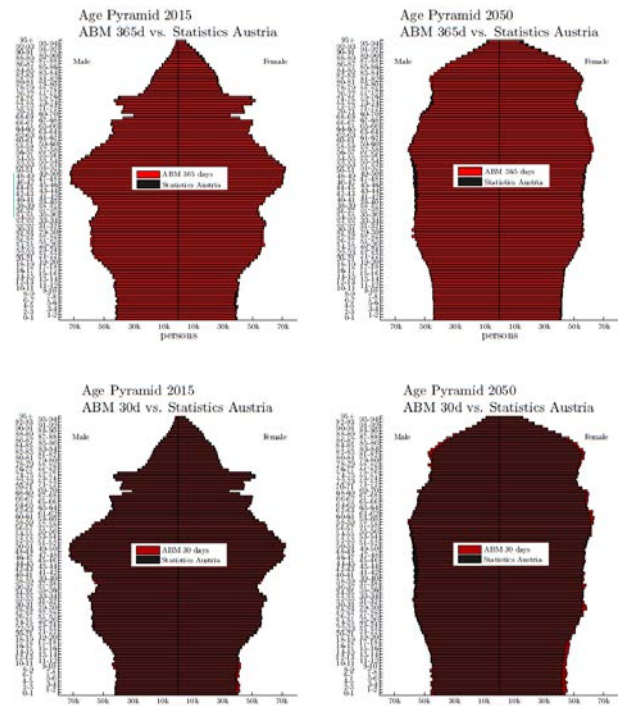


Figure 4: Age pyramid resulting from the model vs. age-pyramid resulting from Statistics Austria data/prognosis. Only for the 365 day execution slight differences can be seen for 0-5 year old women.

3. DETAILED MODEL DEFINITION

In order to fulfil the three tasks described in section 1.2 GEPOC has to be extended by a couple of new functionalities/modules:

- Each agent (statistical representative for a real person) has a possibility to have a hospital stay. Herein it receives a diagnosis which influences how long the patient stays in the hospital and whether the agent might return to a hospital after some time, i.e. has a readmission.
- Each NUTS3 region has a specific mean-driving time to a hospital which influences the re-hospitalization probability for all inhabitants.
- Each person may additionally suffer from Diabetes Mellitus which itself increases the readmission probability.

Moreover GEPOC used as a part of CEPHOS-Link is always executed with the total population of about 8 - 9Mio. Agents (i.e. $K = 1$) to avoid rounding errors and, more importantly, confusions which might lead to a lack of credibility. Moreover yearly steps are used as all input data is given at a yearly basis. Note that yearly steps does not imply that every step is 365 days long (leap-years).

3.1.1. Task A: Hospitalization and re-hospitalization

In addition to the defined agent behavior in the GEPOC section each agent (standing for one representative real person) has a probability to have a called index-stay during each time-step. By this term we refer to the first

hospital-stay of a person (agent) in a year which is not a readmission. I.e. any agent that did not already have a readmission in the observed year has a certain probability

$$Pi(a, s),$$

wherein a, s stand for age and sex of the agent, to visit a fictional hospital at some point during the observed year. Note that this probability, in the contrast to almost all standard GEPOC parameters, does not depend on time. In case the person is (randomly) selected to do so, first of all the agent receives one of two diagnosis: *psychotic* or *nonpsychotic*:

$$P(\text{Diagnosis} = \text{psychotic}) =: Pdp(a, s),$$

$$P(\text{Diagnosis} = \text{nonpsychotic}) =: Pdn(a, s).$$

We will refer to this diagnosis as d henceforth. Dependent on this diagnosis the length of the stay is sampled. This is either done using a gamma-variate random variable or sampling a number of days by a discrete distribution. In any case this duration must exceed one day (one night) by definition:

$$\text{Length of stay}(a, s, d) \sim \Gamma(\alpha, \beta) \text{ or discrete.}$$

Moreover each agent might have a chance to be readmitted at a later point in time. Although this might basically sound acausal, the question whether or not an agent is readmitted is answered immediately at the point of the index stay due to data reasons. Therefore we have a probability

$$Pr(a, s, d)$$

deciding about if an agent is readmitted. In case an agent is chosen to do so two time-spans are sampled, once more either by gamma-variate random numbers or by discrete distributions:

$$\text{Time until readmission}(a, s, d) \sim \Gamma(\alpha, \beta) \text{ or discrete.}$$

$$\text{Length of readmission} \sim \Gamma(\alpha, \beta) \text{ or discrete.}$$

All of these time-spans must not be shorter than one day (night). The time until readmission must not exceed 365 days.

3.1.2. Task B: Mean Driving Time Influences Readmission Probability

In order to have the re-hospitalization probability depend on the mean driving time to a hospital in a specific NUTS3 region, the NUTS3 extended GEPOC version (described before) is used. Moreover let r define the region an agent inhabit and $F(r)$ a specific factor that indicates how much higher the probability for a readmission for a specific NUTS3 region r is. In most cases two NUTS3 regions were identified, that have a significantly higher readmission rate than the rest. Hence $F(r) > 1$ for two regions and 1 for all others. We receive:

$$Pr(a, s, d, r) = F(r) \cdot Pr(a, s, d) \cdot K,$$

for a constant compensation factor K (slightly smaller than 1) which had to be calibrated, so that the new

simulation results do not differ from the old ones in total (total Austria).

All other parts of the model remained untouched.

3.1.3. Task C: Diabetes Mellitus

Given only the total prevalence of diabetes in Austria, Veneto and Slovenia the model, but not the incidence numbers the model had to be parameterized differently than the hospitalizations – it is not possible to correctly calculate a probability for a diabetes case by knowing only the absolute numbers per year. Therefore the Government Agent (described in the GEPOC Section) takes care about the number of diabetes diseases in the model. It observes the number of diabetes cases (per sex and age cohort) at the beginning of each time-step and randomly “distributes” new diabetes cases randomly among the population to fit the diabetes-prevalence numbers of the actual year. This yet very macabre way of modelling a disease is the only way to use prevalence data to directly parameterize disease models. Otherwise a very demanding calibration process had to be done.

Say an agent's diabetes status D is either *true* or *false* and $F_2(D)$ ($= 1$ for *false*, > 1 for *true*) denotes the influence of diabetes on being readmitted to a hospital the probability for a readmission is given by the following probability:

$$Pr(a, s, d, r, D) := F_2(D) \cdot Pr(a, s, d, r) \cdot K_2$$

$$= F_2(D) \cdot F(r) \cdot Pr(a, s, d) \cdot K \cdot K_2$$

Once again, a compensating factor $K_2 < 1$ had to be calibrated.

4. PARAMETRIZATION

4.1. Hospitalization Specific Parameters

Without going into detail about data acquisition at this specific stage (it is briefly explained in <somewhere else>) we will only explain which and how data was used to parameterize the model.

First of all probabilities

$$Pi(a, s), Pr(a, s)$$

could be determined using known methods (dividing number of known index-stays or readmissions by total population or total number of index-stays respectively). We chose numbers for 2006 (Austria) and 2013 (Slovenia, Veneto) as reference for these calculations. Age classes 65+ had to be dealt as a whole. This was a matter of the sample size as for certain age classes >65 not even one index-stay was recorded in 2006/2013 which would have perturbed the model parameterization by (definitely wrong) $Pi(a, s) = 0$.

In order to sample a length of a stay or the time between two hospital-stays was initially tried to be fitted by a gamma distribution dependent on age and sex (and diagnosis). Hence two age, sex (and diagnosis) parameters α and β were determined using a standard maximum-likelihood method. In case the gamma-distribution turned out to be a bad match for the given data, a discrete distribution was fitted – i.e. the numbers $P(\text{time interval} = x \text{ days} | s, a, (d)), x \in \{1, \dots, 365\}$

were determined by a histogram. Which method was used for which parameter can be seen in Table 1.

Table 1: Which distribution was used to sample which time-span for all three considered regions

	Austria	Slovenia	Veneto
Length of index-stay	gamma-distributio n	gamma-distributio n	gamma-distributio n
Time until readmission	discrete	discrete	discrete
Length or readmission -stay	gamma-distributio n	discrete	discrete

In the following Figures 5 and 6 exemplarily show the results of the gamma distribution fit, estimated with a Maximum Likelihood estimator.

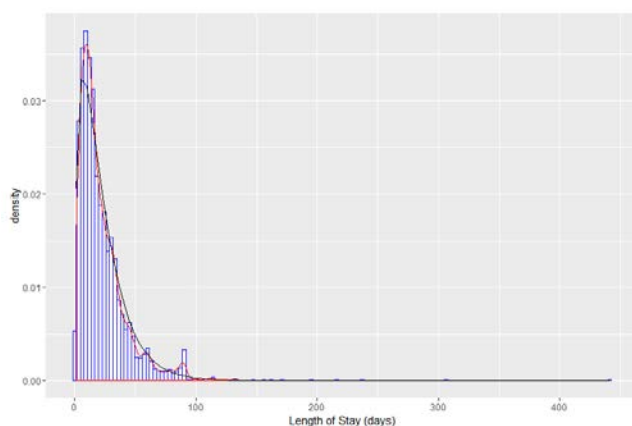


Figure 4: Length of stays according density function (red) overlayed with a gamma density function (black) of the Veneto region patients

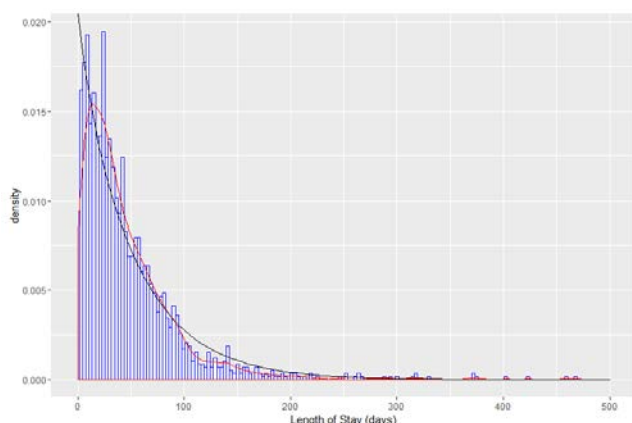


Figure 6: Length of stays according density function (red) overlayed with a gamma density function (black) of the Slovenian patients

4.2. Diabetes Specific Parameters

Diabetes Mellitus (DM) prevalence data was available for two specific points in time:

- Total number of DM cases for 2010 and Austria, Slovenia and Italy/Veneto with following subcategories: No. of Female Cases,

No. of Male Cases, No. of cases [20-39], No. of cases [40-59], No. of cases [60,79]

- Total number of DM cases (estimation) for 2030 and Austria, Slovenia and Italy with following subcategories: No. of Female Cases, No. of Male Cases, No. of cases [20-39], No. of cases [40-59], No. of cases [60,79]

In order to use the data for parameterization of the model, the following pre-processing was performed. As the model requires a finer resolution than the given data some assumptions had to be made as well.

- Assumption: Age and sex are (approximately) independent parameters
 - Calculated total number of diabetes cases per age cohort and sex based on marginal distributions
- Assumption: Total case numbers behave approximately linearly with time
 - Total numbers for cases linearly inter/extrapolated based on data for 2010 and 2030.
- Assumption: Diabetes cases are homogenously spread among Italy (i.e. Veneto cases can be scaled using the Veneto/Italy fraction)
 - Divided Population-numbers for Veneto by Italy (per year and sex gained from EUROPOP2013). Used this fraction to get case numbers for Veneto
- Diabetes cases per person (or per 10000) is a number that behaves linearly with age.
 - Gain diabetes cases per person for age cohorts [0,20) and [80+] by linear extrapolation from the other three available age classes [20,40), [40,60), [60,80). Finally gained total number of diabetes cases by re-multiplying these numbers with the population.

5. RESULTS

The results are clustered into developed methodological level and the problem solving results gathered using the model and scenario calculations.

5.1. Methodological findings and practical use

The GEPOC model mainly developed for use in Austria within the DEXHELPP consortium is tested to be flexible enough to integrate longer time spans and being parameterized for foreign countries.

During the calibration process a new method for agent based model parameter estimation has been developed (see extra papers in press from main author Martin Bicher) dealing with the problem of long cycle times for single simulation runs and therefore the necessity of fast converging algorithms.

The combination of expert knowledge of different disciplines – especially data scientists, medical doctors with background knowledge on real world treatment, statisticians and modelling experts – has been tested and methods toolkits (available under cephos-link.org) for international claims data usage in the psychiatric disease setting have been performed.

5.2. Simulation results

The results of the simulation scenarios in a aggregated form for 10-years age groups and mapped with the ppp cost data are analysed and depicted exemplarily in Figure 7 for the three countries/regions in parallel and for different age groups of Austria in Figure 8.

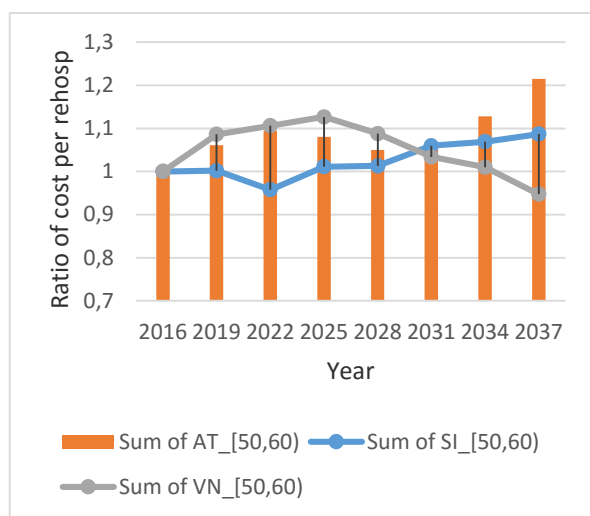


Figure 7: Relative change of the overall costs for re-hospitalizations for the age group of the 50 to 59 years old patients in the three regions in comparison. In each country the costs are inflation affected with the inflation of each country based on the year 2016.

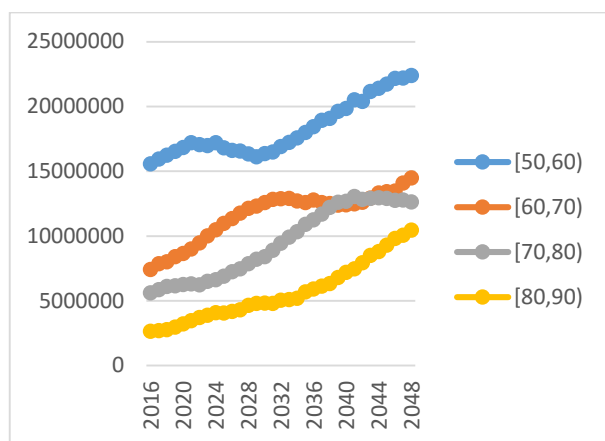


Figure 8 The graph represents the change over the whole simulation time for the Austrian data setting of the overall re-hospitalization costs for the four 10 years age groups between 50 and 90 years based on the Austrian inflation assumption.

6. DISCUSSION

All three scenarios show that psychiatric hospitalizations are rising, especially in Austria and Veneto. The most drastic changes can be assumed to come in the timeframe of the next 10 years for non-psychotic diagnosis.

Testing changes on treatment structures like distance to services and calculating corresponding what-if scenarios also provides more insight on effects of these interventions. Changing diabetes prevalence also has an impact on psychiatric patients' re-hospitalisation and shows that comorbidities should not be neglected when analysing future development of re-hospitalisation rates.

To gain more detailed results, the developed model provides a profound basis for integration of further modules. It is well suited for the implementation of patient pathways through the system, following their multiple re-hospitalisations as well as ambulatory treatment. For planning and testing new treatment strategies and/or structural changes, the simulation model can be extended, in order to assess the impact of such interventions and therefore, to optimize their implementation for different restrictions, like ethical or budget limits. Different expert opinions and can be tested in scenarios and the effect identified in testing regions can be expanded to the whole computer based test environment.

Altogether, we conclude that the model works well for the defined questions, but to improve prognosis quality further data and especially assumptions on causal relations are desirable. The implementation of the agent-based approach in the modular design for the CEPHOS-LINK model is flexible enough to suffice these further requirements and with improved data quality as well as more actual data provide can provide more insight on the development of both index- and re-hospitalisation rates. The parameterization of the model shows that the countries share similar properties from a qualitative point of view which is in itself an interesting result. It shows that although there are quantitative differences the countries probably share the same causal relations in the background which lead to hospitalisation and re-hospitalisation rates.

An interesting part for future model based evaluations is therefore integration of even more interdisciplinary knowledge also from social sciences, experts on plans of changing treatment infrastructure and different guidelines. Utilizing such a simulation model correctly then may prevent unexpected treatment bottlenecks and help decision makers to optimize allocation of their resources for better treatment of psychiatric patients.

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