Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

PHASE: FACILITATING AGENT-BASED MODELLING IN POPULATION HEALTH

Eric Silverman
Umberto Gostoli

MRC/CSO Social and Public Health Sciences Unit
University of Glasgow
200 Renfield Street, Top Floor
Glasgow G2 3AX, UK

ABSTRACT

Agent-based modelling (ABM), despite numerous successes in various disciplines of the physical and natural sciences, remains at the fringes of population health research. ABM can contribute to public health policy-making by providing a means to develop and test ambitious policies on virtual populations prior to roll-out, and to incorporate detailed individual-level modelling of relevant behavioral processes. Here we introduce PHASE: Population Health Agent-based Simulation nEtwork, a research network started in October 2019 and funded by the UK Prevention Research Partnership that will develop and support the community of agent-based modellers in population health. We then present a worked example of ABM being applied to social care provision in the United Kingdom, demonstrating how our model facilitates the development of complex policy interventions in this area. We propose that ABM for population health research can thrive when underpinned by a strong collaborative network and supported by open-source tools and exemplar models.

1 INTRODUCTION

Population health has been slow to adopt agent-based modelling, despite an increasing focus on developing complex behavioural interventions to influence health outcomes. The field has increasingly adopted a systems-based view of health, in which health outcomes are generated by interacting determinants, including social, economic, political, and environmental factors. Recent position papers have highlighted the potential for using ABM to generate models that simulate these interactions (Rutter et al. 2017; Silverman 2018), yet ABM-based studies in the field remain relatively uncommon.

Traditional epidemiological methods, including statistical modelling, microsimulation and causal inference modelling, face substantial challenges from the 'wicked problems' of population health (Andersson et al. 2014). Wicked problems include widespread health issues such as obesity, drug misuse, and persistent health inequalities – issues that strongly influence population health, and are not responsive to straightforward interventions. These problems are characterised by inter-related, non-linear determinants operating at the individual, institutional, governmental, and population levels (Galea et al. 2010). Traditional methods struggle to model these interactions, given that they do not simulate the actions and interactions of individuals explicitly.

Some opposition to the approach arises from a tendency to compare ABM studies on a like-for-like basis with traditional epidemiological models, despite profound differences in their construction, implementation and underlying assumptions (Murray et al. 2017). Further challenges arise due to the relative lack of computational modelling expertise within public health, and few opportunities for early-career population health researchers to gain experience in simulation methods (Silverman et al. 2020).

We propose that ABM should be more widely utilised in global research efforts to address the 'wicked problems' afflicting society today. ABMs directly simulates the actions of individuals and their interactions with their environment, and in the process allows policy-makers to develop and evaluate interventions including behavioral, social, and economic elements. Addressing the wicked problems of population health requires ambitious policy-making that takes into account the impact of individual-level behavior and the possibility for unanticipated *spillover effects* of otherwise well-intentioned interventions. ABM enables the construction of models that allow the exploration of these complex interactions.

However, in order to facilitate the adoption of ABM in population health, modellers must address the critical challenges outlined above: misconceptions regarding the aims and capabilities of ABM relative to traditional approaches; and a relative lack of simulation expertise within population health. We propose that coordinated efforts at education and training, in combination with open-source tools and exemplar models, can enable population health researchers to more easily incorporate ABM in their modelling toolkit.

1.1 The PHASE Network

The PHASE Network (http://www.phasenetwork.org/) is a four-year project funded by the UK Prevention Research Partnership focused on supporting and enabling agent-based modelling within population health. Network membership includes simulation modellers, computer scientists, epidemiologists, network scientists, epidemiologists, public health researchers, practitioners, policy-makers and industrial partners. The network's Advisory Board includes senior academics, industrial partners and policy-makers, to ensure that network events and training are developed in an inclusive and accessible way, and to take into account the varying perspectives of our diverse membership.

PHASE will support the development of agent-based modelling in population health through a comprehensive set of initiatives:

1. Building and supporting interdisciplinary simulation teams via network events and dissemination of relevant training materials and information.
2. Enabling methodological innovation by providing open-source modelling tools and comprehensive guidance for new modellers.
3. Training researchers, policy-makers and industrial partners in agent-based modelling techniques through courses, online resources and worked examples.
4. Facilitating the development of population health ABM projects via an online model-sharing database for health-related ABMs, and the provision of seed funding for small projects.

PHASE is in its early stages, and the success of this network will depend upon the participation and engagement of our membership. By providing training events, exemplar models, and direct support for ABM projects, we aim to overcome the present obstacles to wider ABM adoption in population health. PHASE seed funding will encourage policy-makers, industrial collaborators and academics to get involved in small ABM projects and reduce the barrier to entry. Ultimately, PHASE aims to develop a collaborative network that brings together previously scattered pockets of ABM work in population health, and fosters a cohesive ABM community in the field even beyond the end of PHASE funding in 2024.

We note that some population health researchers are already embarking on ABM studies (particularly in some areas, e.g., obesity modelling and epidemiology). However, these projects have not triggered a wider uptake of ABM across the discipline, and tools and practices are typically developed in isolation among scattered research groups. Here PHASE aims to contribute by developing a collaborative network that brings together these pockets of ABM work, and fosters a cohesive ABM community in population health.

1.2 An Exemplar Model: Simulating Social Care

As part of the PHASE initiatives to support ABM in population health, we will provide worked examples of ABM being put to use to examine challenging areas of population health research, with open-source code and documentation.

Below we highlight one worked example: a comprehensive and detailed model of social care. This simulation builds upon models initially developed in 2010-2015 as part of the EPSRC-funded Care Life Cycle Project (Noble et al. 2012; Silverman et al. 2013). The model has been developed in Python, and source code is available with a permissive licence via GitHub repositories. Over time we will pair these resources with detailed documentation and modelling guidance, to enable aspiring modellers to make use of our code as they see fit and develop new models based on this framework.

2 MODELLING SOCIAL CARE

2.1 Social Care in the UK

The aged population of the UK contains substantial numbers of people requiring assistance on a daily basis due to persistent ill health and frailty. While government-provided formal care is essential for these individuals, a significant fraction of care is provided informally via family members. As social care costs rise due to an increasing elderly population, UK social care policy-makers face a steadily increasing demand for social care services, and in turn must find ways to support and facilitate informal social care provision in order to ease the strain on public finances.

Informal social care is vital to care provision in the UK, with UK informal care having an estimated value of £100 billion per annum (National Audit Office 2018). In 2016 there were an estimated 5.3 million informal carers in the UK, 72% of whom provide care to their immediate family, including partners, parents and children (Aldridge and Hughes 2016). Informal care within families is often a collaborative effort, with the typical informal care network consisting of 3-5 members working together to address the care needs of their family members (Tennstedt et al. 1989).

Even with this substantial population of informal carers working to address care needs throughout the country, UK social care provision remains insufficient. The supply of carers is dropping gradually due to falling birth-rates (Coleman 2002), while Age UK estimates that nearly half of all elderly people over 75 years of age are living with one or more long-term limiting illnesses (Age UK 2017). As a consequence of this dwindling supply and overwhelming demand, a substantial fraction of social care needs are going unmet. Age UK reported in 2017 that 1.2 million elderly people with care needs received insufficient care (Age UK 2017). In order to meet the rising demand, the population of informal carers would need to rise by 40% over the next two decades (Carers UK 2015).

The rising demand on the social care system generates significant problems for the health care system. A particular problem in the UK context is *bed-blocking*, in which vulnerable patients in need of social care upon release from hospital are unable to return home due to a lack of appropriate social care availability. This then leads to longer hospital stays and shortages of beds for other patients. Bed-blocking is rising in tandem with social care demand, and Age UK reports that the number of additional days in hospital stays attributable to a lack of social care availability increased by 18.7% between 2010-16 (Age UK 2017). In total, bed-blocking reached 2.7 million bed-days per annum in 2016, costing the National Health Service £820 million.

In summary, the rising demand for social care in the UK has significant impact not only on the care sector, but on the lives and livelihoods of informal carers, and the availability of hospital beds and facilities for other patients. Social care depends on contributions from the public and private sectors and from millions of unpaid carers. Consequently, we view social care as a particularly relevant process to examine with ABM, which can explicitly model the efforts of individual carers, the complex lives of vulnerable people, and the many and varied impacts of social and economic policy changes. In the context of PHASE, we will use this work to demonstrate the utility of building detailed and ambitious models of critical challenges in population health.

From the perspective of government, meeting the care needs of the UK population requires policy-making that supports and facilitates informal carers, taking account of the varied challenges care provision presents for families. Our agent-based model fills this need by simulating the complex interactions between individual circumstances and the surrounding economic and social conditions, thereby providing a platform for developing ambitious and comprehensive social care policy. The explicit modelling of individuals, their kinship networks, and individual social and economic circumstances will enable the model to reveal potential *spillover effects*, where policy decisions may have unintended side effects for particular groups of carers or care recipients.

We wish to note here that at the time of writing, the COVID-19 pandemic is having profound effects on the care sector in the UK. Currently the situation is constantly evolving, and the long-term consequences of the virus and its impact on the care sector are still unknown. Future iterations of the social care model will take this into account, and ensure that our framework is able to evaluate social care policies in light of any social, economic and demographic changes caused by the pandemic.

2.2 The Social Care Model

The simulations we present below are re-implementations and substantial extensions of previous modelling efforts aimed at social care supply and demand (Noble et al. 2012; Silverman et al. 2013; Silverman 2019). In this section we will show how this modelling framework has progressed over time, incorporating additional processes that influence care according to input received from policy-makers and social care experts. The models simulate care provision as a complex negotiation process conducted between members of a household and kinship network, with each member being influenced by the surrounding social and economic conditions. What follows is a very brief summary of the core functionality of the modelling framework, common to all three versions.

2.2.1 Core Model Functionality

Agents in these models exist in a virtual space designed to roughly emulate UK geography. The simulated UK includes towns that consist of individual households; the towns have population density in proportion to UK demographics.

The simulation runs in one-year steps and starts in the year 1860, to allow the simulation to run through several generations before we begin collecting data; allowing the model to run for a few generations allows the population dynamics to converge to a more realistic pattern. UK Census data is incorporated into the model from 1951 to ensure realistic fertility and mortality rates. Throughout the run detailed statistics on care provision, receipt, and numerous demographic and economic measures are collected.

2.2.2 Agent Life-Course

Agents follow a life-course reflective of typical life-course transitions observed in UK society. Agents are defined as dependant children from birth until age 16, then may choose to continue in education or enter the workforce. They then make further choices between education and the world of work every two years until age 24. While in work, agents can gain or lose employment and seek out new jobs elsewhere. Working agents receive an income and pay tax; at the age of 65, they retire and receive their pension. Mortality is determined by a Gompertz-Makeham mortality model until 1951, at which point rates from the Human Mortality Database are used. From 2009 we use a Lee-Carter model to approximate future mortality rates.

Adult agents are able to form partnerships with other agents and have children (for simplicity we only generate male-female partnerships, and we assume these partnerships may produce children). Agents are paired up based on probabilities influenced by their differences in age, physical distance and socioeconomic status. Some partnerships dissolve each year according to age-specific probabilities derived from data from the UK Office for National Statistics.

2.2.3 Domestic Migration

Agents in the model are able to migrate domestically in response to certain life-course changes: when they first leave home at adulthood; upon changing jobs; or upon forming a partnership. When partnerships dissolve, we assume that the male agent leaves to form a new household while any dependent children remain with the mother. An important aspect of migration relevant to care provision is that retired agents may elect to move in with their adult children, if they have care needs and their children's household is able to provide care.

2.2.4 Agent Care Needs

By default agents start life in a healthy state, but may enter different care need levels according to probabilities that vary by age and gender. Table 1 provides a summary of the five care need levels and the amount of care required per week in each (both these inputs and those for the amount of care supply in Table 2 below have been informed by discussions with demographers at the University of Southampton, where the original version of the model has been developed). As observed in reality, agents who develop care needs do not recover to normal health, but instead tend to progress to higher levels of need as they age. An agent's likelihood of developing additional care needs increases in proportion to the amount of unmet care need they have. Agents' care need level also influences their mortality, alongside other factors including age and socioeconomic status.

Table 1: Care need categories, with the number of hours of care required per week.

Care need category	Weekly hours of care required
None	0
Low	8
Moderate	16
Substantial	32
Critical	80

Informal social care is provided through an agent's kinship network, which consists of the households having some familial relationship with the care receiver. We assume in this model that if agents have time or income available, they will provide informal care or pay for informal care for the agent in need. Care provision amounts vary by socioeconomic status, the closeness of their kinship, and the spatial distance between provider and receiver.

2.2.5 Socioeconomic Status

Agents can be in five different socioeconomic status groups (SES groups), derived from the Approximated Social Grade presented by the UK Office for National Statistics. We calibrated the model to roughly reflect the UK's SES distribution in 2016; see Gostoli and Silverman (2019) for further details. SES groups affect several key life-course processes: agents in higher SES groups have lower fertility and mortality rates; higher salaries; greater wealth; are less likely to transition into higher levels of care need; and may allocate more income to care provision. Education can enable agents to progress into higher SES groups.

2.2.6 Kinship Networks

As mentioned above, agents are part of kinship networks consisting of the network of households with which the they have a familial relationship. Kinship can be of varying degrees, and is measured by the network distance between households within the kinship network (with a value ranging from zero to three). When care is being supplied to an agent, the amount of care available within its kinship network is determined by the size of the kinship network itself, the degree of kinship between the network members, and the individual status of each providing agent. We further assume that only agents in the same town as the recipient can provide informal care, and that private care will only be paid for by close relations (between parents and children). Table 2 provides a summary of the hours of care that can be provided by each category of agent at each kinship level.

Table 2: Care supply by agent status and kinship distance.

Agent status	Household (D-0)	D-I	D-II	D-III
Teenager	12	0	0	0
Student	16	8	4	0
Employed	16	12	8	4
Retired	56	28	16	8

2.2.7 Migration Decisions

Both kinship networks and care availability influence an agent's migration decision-making. Agents prefer to move to town where more of their kinship network is physically present, and where a greater amount of informal care is available to them. In addition, the cost of relocation influences migration decisions; when agents have lived in one place for a long period and have a larger household, they are less likely to move.

2.2.8 Impact of Care Provision on Carers

Agents in employment receive a salary which is based upon its previous work experience and its socioeconomic status. If an agent then decides to reduce its working hours in order to provide informal social care, this in turn reduces the agent's work experience, which over time will reduce its salary relative to agents not providing care.

2.2.9 Formal Care and Publicly-Funded Care

As with informal care, paid-for formal care is provided through an agent's kinship network. If the care-providing agents are in a close kinship relationship, i.e., a kinship distance of zero or one, and they cannot provide informal care, then they can choose instead to pay for formal care. The choice to provide formal care is influenced by the time and income the providers have available for social care. If the hourly wage of the lowest-paid member of the care-providing household is less than the hourly cost of formal care, and the care recipient lives in the same town, then the agent will reduce their working hours and provide informal care; if the hourly wage is higher than the cost of formal care, then the household will pay for formal care instead.

The model contains a simplified publicly-funded social care policy which simulates the current policies in force in the UK; note that a later version of the model specific to Scotland alters this scheme to reflect Scottish social care policy. In this scheme, agents with a care need level of 'critical' and in possession of less than £23,250 of wealth can receive government support; for simplicity we assume that care homes are part of this support rather than representing them explicitly. If the agent's wealth drops below £14,250, then the government pays all social care costs necessary to ensure the agent's income does not drop below £189 per week.

3 EXEMPLAR SIMULATION RESULTS

In this section we present examples of policy comparisons performed with three different variations of the social care modelling framework outlined above. These results will demonstrate how detailed agent-based models of social care processes enables us to generate insightful comparisons of possible social care policies.

In each subsection below, we will describe briefly each version of the model and its evolution from the previous, and present a policy comparison generated by each version. This modelling process will inform the examples and guidance to be presented during the PHASE Project, and will demonstrate how complex agent-based models can be built with relevance to difficult real-world policy questions that bear on significant challenges in population health.

3.1 Model I: Social Care Provision with Kinship Networks

This model was presented initially in Gostoli and Silverman (2019), and utilises all the simulated processes outlined above. For implementation details, please see the model code archived in (Gostoli 2019b). We considered two policy interventions: the introduction of fully tax-deductible social care expenses; the reduction of the government-funded social care eligibility criteria from the Critical care need level to the Substantial care need level (see Table 1).

The first intervention is equivalent to a reduction of the cost of formal social care, as part of the price will be indirectly paid by the government. Given the progressive taxation system, the cost reduction will tend to be higher for individuals with higher incomes. The second intervention relaxes the eligibility criteria for receiving government-funded social care. The two interventions are implemented in simulation year 2020, and their effects on a number of outcomes are compared to those associated with the benchmark (i.e., the *no-intervention*) scenario.

The next three figures show the cumulative changes over the period 2020-2050 for, respectively, the total social care received, the share of unmet care need and the policies' cost. Figure 1 shows that both policies have a positive impact on total social care received, with the tax deduction intervention having a stronger effect than the relaxation of public care eligibility. Accordingly, Figure 2 shows that the reduction of the share of unmet social care need is greater with the former policy than with the latter. Figure 3 shows that the tax deduction intervention has the greatest effect on unmet care need, but is also the most expensive.

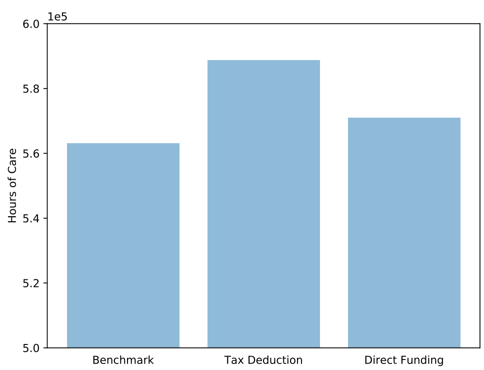

Figure 1: Total social care received.

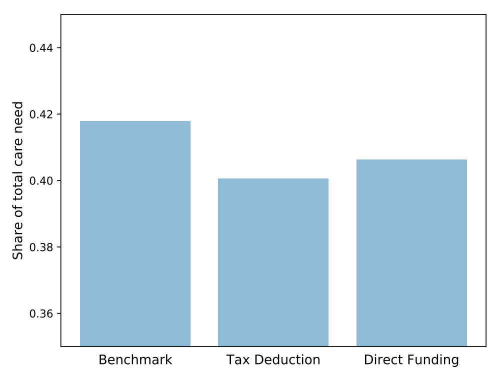

Figure 2: Share of unmet social care.

In order to compare the *effectiveness* of policy interventions, we consider their relative ICER (which we refer to as RICER). In Figure 4 we can see that the 100% tax deduction intervention is the most cost-effective intervention as it reduces by 1% the share of unmet care need with an increase of about 5% in public expenditure, whereas with the first policy we would need to increase the pre-intervention public expenditure by 19% to get the same 1% reduction of the share of unmet social care.

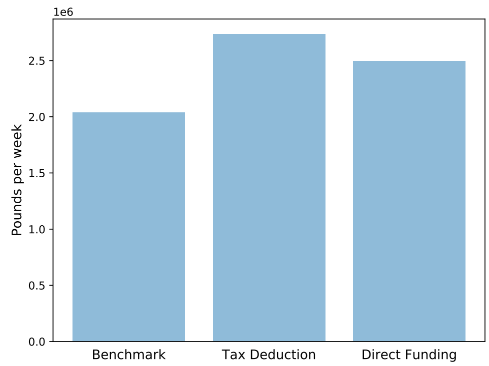

Figure 3: Total policy cost for each policy scenario.

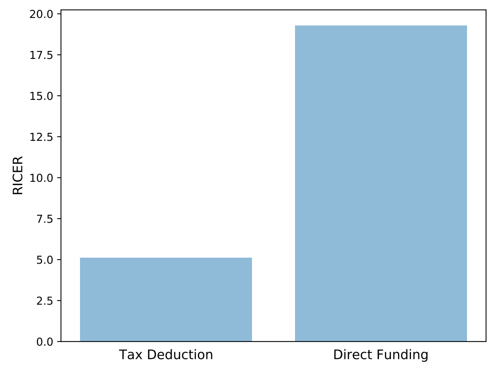

Figure 4: Cost-effectiveness of 'tax deduction' and 'direct funding' policy interventions.

3.2 Model II: Social Care Influenced by Child Care

In this model, we incorporated an additional child care process into the model, following consultation with domain experts. Child care obligations have a significant influence on the availability of informal social care, given that child care obligations carry force of law – beyond the moral and ethical obligations of informal adult social care – and typically consume a large proportion of available care supply. For more details on the implementation, please see Gostoli and Silverman (2020), and the model code on GitHub (Gostoli 2019a).

We investigated the effects of four policy interventions designed to reduce the overall social care burden to UK society. While these interventions affect a single type of care at a time, the relation between child and adult social care provision generates spillover effects (i.e. child care policies affect social care provision and vice versa). The four policy levers targeted by our interventions are as follows:

- Policy 1: increase public child care cost contribution from 20% to 80%
- Policy 2: increase free child care for children aged 3 and 4 from 20 to 32 hours/week
- Policy 3: reduce government-funded social care eligibility criteria from the Critical care need level to Substantial
- Policy 4: introduction of a government contribution of 50% of the cost of social care

As with the first model, we implement the four policies from simulation year 2020 and compare the outputs of these four policy scenarios with the benchmark 'no-change' scenario over the period 2020–2050.

Figure 5 shows how a policy meant to affect primarily child care provision (i.e., Policy 1) produces positive effects on unmet social care which are similar to a social care intervention (i.e., Policy 4), a clear example of a *spill-over effect*. There are two main causes of this effect: first, as child care becomes cheaper under Policy 1, households are more able to pay for formal child care rather than providing informal child care, so that more time will be available for informal social care; second, increased financial resources become available for formal social care, due to the reduced cost of formal child care. This figure shows that the other two policies also have a positive, though smaller, effect on unmet social care need.

Figure 6 shows the policies' total costs over the period 2020-2050. Policy 1 is the most expensive policy, followed by Policy 4, a result which, together with their effects on unmet social care, indicates the higher effectiveness of Policy 4 compared to Policy 1.

Figure 7 shows the effects of the four policies on the total social care need in the period 2020-2050. We can see that Policy 1 reduces the unmet care need by reducing the social care demand (which Figure 7 shows to be lower in this scenario than in the others), while Policy 4 produces this effect mostly by increasing

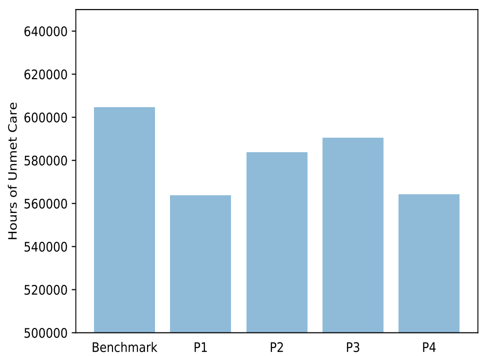

Figure 5: Total unmet care need.

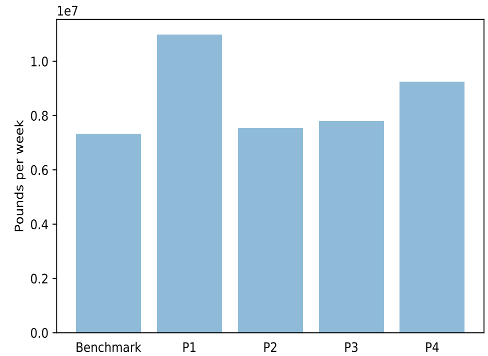

Figure 6: Policies' total cost.

the social care supply. The reduction of social care need obtained by Policy 1 is in turn an effect of the reduction of unmet care need, given that the probability of developing more serious health conditions is positively related to the amount of unmet care need.

We can observe from these figures that Policy 4, unlike Policy 1, reduces unmet care need but not social care need overall. This is a consequence of Policy 4 tending to benefit only individuals with social care needs, and mostly those with the highest level of social care need, whereas Policy 1 benefits potentially all families. This in turn means that the additional resources are more likely to be used to provide social care to people who are, on average, at a lower level of care need, reducing the probability that they will develop more serious conditions and therefore reducing the total social care need.

Figure 8 shows the hospitalization costs associated with the five scenarios. In relative terms, the reduction of hospitalization costs reflects quite closely the reduction of unmet care need, as in our model the probability of being hospitalized depends positively on unmet care need. However, the reduction of hospitalization cost for Policy 4 is smaller than what we would expect looking at the unmet care need associated with this policy, which was similar to the level of Policy 1. This highlights that Policy 1 is more effective than Policy 4 in preventing people from developing more serious health conditions and, consequently, is more effective in reducing the hospitalisation probability.

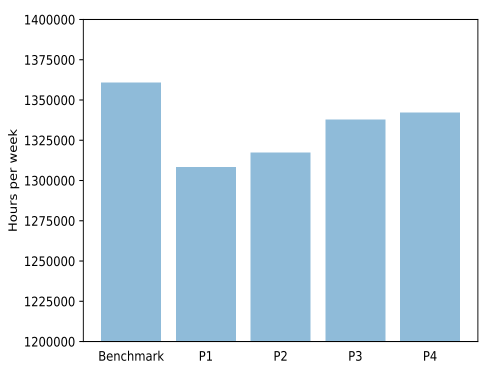

Figure 7: Total social care need.

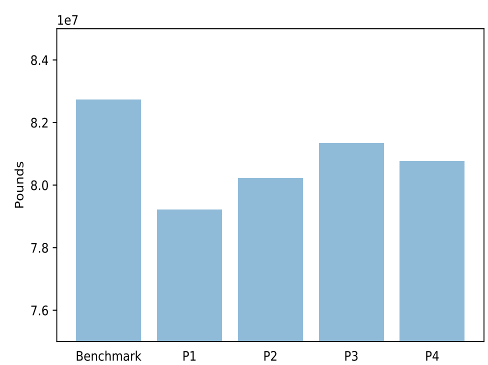

Figure 8: Total hospitalization cost.

3.3 Model III: Social Care in Scotland

In consultation with policy-makers, we have developed a version of the social care model focused specifically on Scottish social care policies. This required substantial modifications, including a different spatial environment to reflect Scotland's geography and population density, the incorporation of variations in publicly-funded care eligibility by local authority, and the free personal care policy in Scotland, in which all adults over 65 years old with care needs are able to access free social care resources. Note that these results are early, and further analysis is forthcoming; for implementation details, please see the relevant GitHub repository (Gostoli 2020).

In these early results we have tested 4 policies:

- Policy 1: the share of public child care contribution rises to 80% (benchmark: 20%)
- Policy 2: the hours of free child care increase to 32 h/w (benchmark: 20 h/w)
- Policy 3: the age limit to receive free social care is decreased to 60 (benchmark: 65)
- Policy 4: the state contributes to 50% of formal social care costs (benchmark: 0)

Figure 9 and Figure 10 show, respectively, the formal and informal social care delivered in the 2020-2050 period. As expected, the reduction of the minimum age for free personal care (Policy 3), reduces both the formal and the informal care which is provided by the recipients' kinship network. In contrast, making formal social care cheaper instead (i.e., Policy 4) tends to increase the quantity provided.

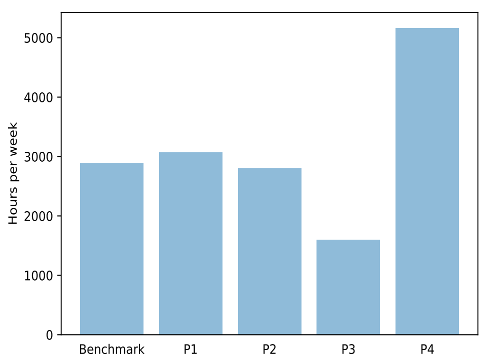

Figure 9: Total formal care.

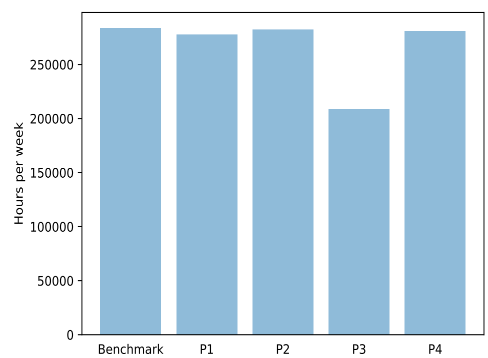

Figure 10: Total informal care.

Figure 11 show the total unmet care demand over the period 2020-50 for the five scenarios. The only policy which seems to have a significant effect on unmet care need is Policy 3, while Policy 4 has a marginal positive effect. These results illustrate two differences between the UK and the Scottish social care system. First, in the Scottish system formal social care is relatively less important than public and informal care, so even a big increase of formal social care (shown in Figure 9 for Policy 4) has a small effect on unmet care need. Second, the Scotland model outcomes do not show significant spillover effects from child care policies to social care provision. In Scotland all those aged 65 or over receive free social care and, considering that this age category represents most of the total social care need, the positive effects of child care policies on social care needs are smaller than in the previous models that cover the entire UK.

Figure 12 shows the total cost in the five scenarios. Although Policy 3 appears to be more expensive than the other policies (and the 'no-change' scenario), its much higher impact on unmet care need and on out-of-work hours make it the most effective policy among those considered.

The calibration of the UK-wide version of the model demonstrated that it could successfully reproduce the patterns of care provision observed across the UK, with appropriate proportions of informal, formal and public care, and of within-household *vs* outside-household care. As this version of the model evolves, we will undertake a similar extensive calibration exercise using the detailed data on informal and personal care available in Scotland. We will also produce detailed sensitivity analyses, as has been done previously for the UK-wide model (Silverman et al. 2013; Gostoli 2019b).

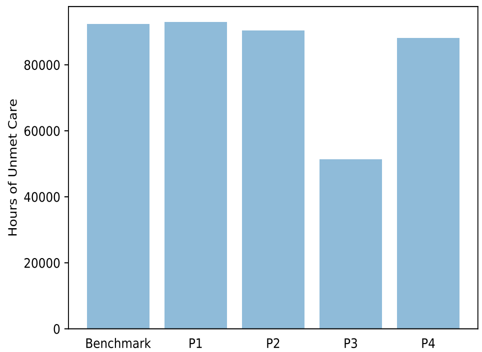

Figure 11: Total unmet care need (2020-2050).

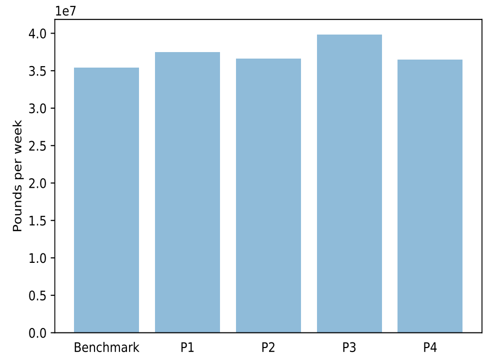

Figure 12: Total policy cost.

4 CONCLUSION

Social care in the UK is a complex and multifaceted problem, influenced by political, social, economic and individual factors. Policy decisions made on this issue will impact not only on care provision and supply, but also health care costs and the well-being of unpaid informal carers. Given the potential for spillover effects from policy interventions, an ABM approach to social care can provide a means to test complex policy interventions prior to roll-out and better understand their impact on other parts of the health and social care systems.

As demonstrated by our extensive modelling work in this area, developing simulations of health and social care is a challenging undertaking. An iterative approach is required, in which modellers gradually construct a modelling framework based on input from stakeholders, domain experts, and policy-makers. The end result, however, is a modelling framework that can simulate detailed policy decisions, and thus allow policy-makers to better judge the possible emergent effects of their decisions.

The PHASE Project will use exemplar models and projects like the above to reduce the barrier to entry into ABM for new modellers in population health and related disciplines. By providing source code, documentation, guidance and best practices, and training opportunities, we will provide modelling frameworks and principles that will help teams get started on their first ABM projects.

PHASE will also provide a means for modellers to connect with policy-makers, so that they can build projects with the potential to influence real-world policy. In the social care modelling project, consultation with social care experts and government policy-makers has been vital to our advancement of this framework. Forming these multidisciplinary, cross-sector collaborative groups will be essential to developing ABMs with significant impact on policy, and will help ensure that ABM is more widely adopted by the population health community.

ACKNOWLEDGEMENTS

Umberto Gostoli and Eric Silverman are part of the Complexity in Health Improvement Programme supported by the Medical Research Council (MC_UU_12017/14) and the Chief Scientist Office (SPHSU14). This work was supported by UK Prevention Research Partnership MR/S037594/1, which is funded by the British Heart Foundation, Cancer Research UK, Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Engineering and Physical Sciences Research Council, Economic and Social Research Council, Health and Social Care Research and Development Division (Welsh Government), Medical Research Council, National Institute for Health Research, Natural Environment Research Council, Public Health Agency (Northern Ireland), The Health Foundation and Wellcome.

REFERENCES

Age UK 2017. "Briefing: Health and Care of Older People in England 2017". https://www.ageuk.org.uk/globalassets/age-uk/documents/reports-and-publications/reports-and-briefings/care--support/the_health_and_care_of_older_people_in_england_2017.pdf, accessed 14th July.

Aldridge, H., and C. Hughes. 2016. *Informal Carers and Poverty in the UK*. London, UK: New Policy Institute. https://www.npi.org.uk/publications/income-and-poverty/informal-care-and-poverty-uk/, accessed 14th July.

Andersson, C., A. Törnberg, and P. Törnberg. 2014. "Societal Systems – Complex or Worse?". *Futures* 63:145–157.

Carers UK 2015. "Facts and Figures". https://www.carersuk.org/news-and-campaigns/press-releases/facts-and-figures, accessed 14th July.

Coleman, D. 2002. "Replacement Migration, or Why Everyone is Going to Have to Live in Korea: A Fable for Our Times from the United Nations". *Philosophical Transactions of the Royal Society B* 357(1420):583–598.

Galea, S., M. Riddle, and G. A. Kaplan. 2010. "Causal Thinking and Complex System Approaches in Epidemiology". *International Journal of Epidemiology* 39(1):97–106.

Gostoli 2019a. "UmbertoGostoli/CareSim—-Informal-and-Formal- Child-and-Social-Care: Child and Social Care Model - Parameters from files [v0.8]". Zenodo: https://doi.org/10.5281/zenodo.2592521, accessed 14th July.

Gostoli 2019b. "UmbertoGostoli/Population-Health-and-Care-Model: New core ABM framework with scenario generation and policy comparison II [v0.6]". Zenodo: https://doi.org/10.5281/zenodo.2592385, accessed 14th July.

Gostoli 2020. "UmbertoGostoli/Simulation-for-Scottish-Gov: Social Care Scotland". Zenodo: https://doi.org/10.5281/zenodo.3769179, accessed 14th July.

Gostoli, U., and E. Silverman. 2019. "Modelling Social Care Provision in An Agent-Based Framework with Kinship Networks". *Royal Society Open Science* 6(7):190029.

Gostoli, U., and E. Silverman. 2020. "Social and Child Care Provision in Kinship Networks: an Agent-Based Model". *arXiv e-prints*:arXiv:2002.05188.

Murray, E. J., J. M. Robins, G. R. Seage, K. A. Freedberg, and M. A. Hernán. 2017. "A Comparison of Agent-Based Models and the Parametric G-Formula for Causal Inference". *American Journal of Epidemiology* 186(2):131–142.

National Audit Office 2018. "Adult Social Care at a Glance". https://www.nao.org.uk/wp-content/uploads/2018/07/Adult-social-care-at-a-glance.pdf, accessed 14th July.

Noble, J., E. Silverman, J. Bijak, S. Rossiter, M. Evandrou, S. Bullock, A. Vlachantoni, and J. Falkingham. 2012. "Linked Lives: The Utility of an Agent-Based Approach to Modeling Partnership and Household Formation in the Context of Social Care". In *Proceedings of the 2012 Winter Simulation Conference*, 1046–1057. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Rutter, H., N. Savona, K. Glonti, J. Bibby, S. Cummins, F. G. Diane Finegood, L. Harper, P. Hawe, L. Moore, M. Petticrew, E. Rehfuess, A. Shiell, J. Thomas, and M. White. 2017. "Why We Need a Complex Systems Model of Evidence for Public Health". *The Lancet* 390(10112):2602–2604.

Silverman 2019. "thorsilver/ABM-for-social-care: v1.0 – First release version [v1.0]". Zenodo: https://doi.org/10.5281/zenodo.2591036, accessed 14th July.

Silverman, E. 2018. "Bringing ALife and Complex Systems Science to Population Health Research". *Artificial Life* 24(3):220–223. PMID: 30485143.

Silverman, E., U. Gostoli, S. Picascia, J. Almagor, M. McCann, R. Shaw, and C. Angione. 2020. "Situating Agent-Based Modelling in Population Health Research". *arXiv e-prints*:arXiv:2002.02345.

Silverman, E., J. Hilton, and J. Bijak. 2013. "Simulating the Cost of Social Care in an Ageing Population". In *Proceedings of the 27th European Conference on Modelling and Simulation*, 689–695. Dudweiler, Germany: European Council for Modeling and Simulation.

Tennstedt, S. L., J. B. McKinlay, and L. M. Sullivan. 1989. "Informal Care for Frail Elders: The Role of Secondary Caregivers". *The Gerontologist* 29(5):677–683.

AUTHOR BIOGRAPHIES

ERIC SILVERMAN is a Research Fellow in the Complexity programme at the MRC/CSO Social and Public Health Unit at the University of Glasgow, and leads the Modelling Complex Systems workstream in the Complexity programme. He holds a PhD from the School of Computing at the University of Leeds. His email address is eric.silverman@glasgow.ac.uk.

UMBERTO GOSTOLI is a Research Associate in the Complexity Programme at the MRC/CSO Social and Public Health Sciences Unit at the University of Glasgow. He holds a PhD in Economics from the University of Bologna. As part of the Modelling Complex Systems workstream, he develops agent-based models of socio-economic systems. His email address is umberto.gostoli@glasgow.ac.uk