Uncertainty Analysis in Population-Based Dynamic Microsimulation Models: A Review of Literature

Miia Rissanen[1,2] and Jyrki Savolainen[1,3]
[1]Lappeenranta-Lahti University of Technology, Yliopistonkatu 34, Lappeenranta, Finland
[2]Keva, Unioninkatu 43, Helsinki, Finland
[3]CSC – IT Center for Science, Tehdaskatu 15, Kajaani, Finland

Keywords: Dynamic Microsimulation, Population-Based Modeling, Uncertainty Analysis, Monte Carlo Simulation.

Abstract: This paper reviews population-based dynamic microsimulation (DMs) models used in policy analysis and decision support of social systems and demographics. The application of uncertainty analysis (UA) methods is examined focusing on how probabilistic Monte Carlo (MC) simulation technique is being used and reported. Secondly, inspired by the expanding possibilities of data, this analysis examines the models' capability to uncover finer temporal variations beyond traditional yearly intervals and the use of near real-time data in the reported studies. The analysis of the 44 studies included in this preliminary literature review reveals a lack in the rigorous application of UA and transparent communication of results, particularly in the social sciences. Despite the advances of data availability and modeling, no research attempts were found that would indicate a shift of paradigm from historical data-driven models to real-time data. It is suggested that DM studies in this context could benefit from some mutually agreed standardized reporting guidelines for UA. This literature review serves as a preliminary exploration of the topic, highlighting the need for a more comprehensive and systematic survey to thoroughly assess the current state of research.

1 INTRODUCTION

Dynamic microsimulation (DM) models are analytical tools to simulate the behavior of individual units over time and predict recurring events based on historical data. These models integrate data analysis, computational methods, and computer experiments to support ex-ante policy analysis, government planning and decision making. (Brown & Harding, 2002; Harding, 2007; O'Donoghue, 2014; O'Donoghue & Sologon, 2023; Sauerbier, 2002; Spielauer and Duplirez, 2019). Throughout the simulation, each micro-unit, representing diverse population characteristics (e.g., age, employment, health status), evolves independently through stochastic processes, with their states updated over time according to current conditions and attributes—a phenomenon referred to as "dynamic aging" (see e.g., Burgard et al., 2020; Dekkers, 2015).

Many popular DMs (see in detail e.g., Harding, 2007; O'Donoghue, 2001) were initially developed to address concerns about population aging and to assess affordability of the future social protection system. Over the last decade, their applications in health and labour market studies have been growing (O'Donoghue & Dekkers, 2018). Unlike population-aggregating macroscopic approaches, DMs consider individuals separately, which is crucial for understanding the complex interconnections between factors such as demographics, education, employment, and health that influence future economic and health outcomes. For a general introduction to DMs and their applications, the reader is advised to refer to, e.g., O'Donoghue (2001, 2014), O'Donoghue and Dekkers (2018), Klevmarken (2008), and Zaidi and Rake (2001).

Times of uncertainty, such as the Ukraine war, COVID-19 and past financial crises, have created new demands for real-time simulation and "nowcasting" (O'Donoghue & Sologon, 2023; see also Navicke et al., 2014) to facilitate timely decision-making in rapidly evolving economic landscape. Digital trace data from web browsing and mobile applications provide unprecedented regional and temporal data granularity, enabling close-to-real time modeling of social phenomena, such as predicting disease spread (Burgard et al., 2021; Kashyap & Zagheni, 2023; Li et al., 2024; O'Donoghue &

Rissanen, M. and Savolainen, J.
Uncertainty Analysis in Population-Based Dynamic Microsimulation Models: A Review of Literature.
DOI: 10.5220/0012995200003838

In *Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2024) - Volume 3: KMIS*, pages 74-84
ISBN: 978-989-758-716-0; ISSN: 2184-3228

Dekkers, 2018). With more real-time data, simulation models could better capture short-term fluctuations instead of producing predictions only on an annual level, thus hiding seasonal variations and timely insights, e.g., related to healthcare demands or labour force participation. However, it seems common that administrative data used in many popular DMs targeted to public policy analysis (see again e.g., Harding, 2007) typically has a time lag (O'Donoghue & Sologon, 2023), even if such data is generated constantly as by-products of administrative transactions.

Despite the data revolution enhancing simulation capabilities (Crato, 2023; Margetts & Dorobatu, 2023; O'Donoghue & Sologon, 2023), the proper accounting of modeling uncertainty in DMs remains challenging. To address the inherent stochasticity when simulating individual behaviour and demographic and economic changes is complex, particularly given the (too) high expectations for perfect modeling accuracy (Burgard and Schmaus, 2019; Gilbert et al., 2018; O'Donoghue, 2014; O'Donoghue & Dekkers, 2018; Sharif et al., 2012, 2017). In modeling studies, this often shifts the focus from probabilistic thinking back to traditional, deterministic scenario analysis with single-point estimates, although it is well-known (see e.g., Burgard and Schmaus, 2019; Sharif et al., 2012) that for DMs to be useful, they must thoroughly analyze potential impacts on populations under various scenarios. It's crucial to examine not just the outcomes but also the processes leading to them, incorporating comprehensive uncertainty analysis (UA) of various sources of variation. The authors discussing uncertainty and stochasticity in demographic modeling include Alho and Lassila (2023), Xue et al. (2021), Sabelhaus and Topoleski (2007), and Lee and Tuljapurkar (1994).

Monte Carlo (MC) simulation is a key method for handling uncertainty in DMs, offering a robust approach to systematically explore how variations in inputs affect model outputs. This numerical method involves random sampling from distributions and repeated simulations using the sampled values. The Markov Chain Monte Carlo (MCMC) method, in turn, draws mutually dependent samples to generate random sequences of state transitions based on probabilistic rules (e.g., from logit models build on historical data). This process is repeated hundreds or thousands of times to simulate the expected behavior of the object of interest over time, with calibration performed at each step using newly generated parameters. As such, the MC simulation mitigates misinterpretations from single simulations by examining a broad spectrum of possible outcomes, thereby capturing the inherent variability in simulated population dynamics (Burgard and Schmaus, 2019; Marois & Aktas, 2021; Rutter et al., 2011). Confidence intervals (CIs) communicate variability in outcomes, with larger sample sizes and higher number of simulation iterations leading to narrower CIs and more precise estimates (Burgard et al., 2020; Smithson, 2003; Spielauer & Dupriez, 2019).

Previous literature reviews and surveys on DMs, such as O'Donoghue (2014), Li and O'Donoghue (2013), and O'Donoghue and Dekkers (2018), provide a comprehensive overview of DMs developed over decades (see also Spielauer, 2007; Zaidi & Rake, 2001). In past reviews, the lack of standardization in reporting practices and incomplete validation of models stay as ongoing topic (see also Burgard & Schmaus, 2019; Lee et al., 2024). However, past studies have not delved deeper into the use of probabilistic methods, specifically MC approach and related reporting in demography DM studies, although best practices of UA have been proposed by e.g., Burgard and Schmaus (2019), Lee et al. (2024) and Caro (2012). Another gap pertains to the scarcity of literature examining whether enhanced data accessibility in terms of granularity and timeliness have spurred advancements in models capable of delivering more accurate and timely forecasts, compared to "traditional" DMs those run simulations in yearly intervals and are initialized using historical data with a time lag of several years (see O'Donoghue & Sologon 2023).

This paper addresses these mentioned gaps by conducting a preliminary literature review using the Scopus Database, targeting publications from 2000 onwards with "Dynamic Microsimulation" and "Population" or "Demography" in the title, abstract, or keywords. The search was limited to peer-reviewed journals, conference proceedings, books, and reviews in English, yielding 158 results. After content analysis, based on the title and abstract, 44 documents focused on dynamic microsimulation modeling works targeted mainly to model demographic dynamics were selected. In this initial review, the focus is on addressing aspects of uncertainty analysis rather than technical details. Thus, technical/model introduction reports about the model construction (e.g., Andreassen et al., 2020; Münnich et al., 2021.) were not reviewed since these do not focus primarily on conducting simulations, but rather introduce e.g., the modules and data requirements. Also, as the focus is primarily on DMs, some publications utilizing combined micro-macro simulations are not included and, duplicates were also excluded.

In the following section, preliminary findings of the review and discussion with the objective to inspect the scale and scope of the MC applications are provided with aggregated knowledge on the conventions such as number of simulations run and the use of CIs. Additionally, the modelers' decisions regarding the number of simulations in MC, and other possible discussion of uncertainty aspects together its mitigation methods are emphasized. Secondly, the review reveals the time span of the forecasts (e.g., annual) and the possible specification of being spatial or agent-based model (ABM). These reflects (from one perspective) to the data aspects in terms of timeliness and granularity. The paper also identifies studies that aim to utilize near real-time information or continuously updating models. Considering future research, other findings related to emerging technologies, mainly ML-oriented works, are acknowledged although this research mainly omits the technical details about the models.

The paper concludes with suggestions for future research. Conclusions are drawn from available publication details, and while the literature review is not comprehensive, it lays the groundwork for a more in-depth study on these schemes.

2 RESULTS AND DISCUSSION

In the following results section and related discussion, the reader may find it helpful to refer to Table 1, which presents basic information of the modeling works (author, year), the brief summary of main modeling purpose and the findings related to the MC simulation and data aspects, as detailed in the previous section. We do not specify whether the MC is used only in some model parts. Also, if the use of MC method is not reported, but repeated simulations are applied, it is categorized under the MC. If other methods are clearly reported, such as bootstrapping, they are marked.

2.1 Results

In most of the reviewed studies (30 out of 44) MC/repeated simulations is applied (see, Table 1). In the set of these 30 studies reporting practices vary: seven works did not directly report on using the MC method, but it was shown that the simulation had been indeed run repeatedly. In 13 entries the number of simulations run was not reported and notably, 16 studies (out of 30) did not report CIs. Yet only two

Table 1: Reviewed studies of DMs. Legend: [MC]=Monte Carlo method used (Yes/No or "-" if unclear and additional NR=not reported, if repeated simulation applied without reporting the method or "B" if bootstrapping is applied instead of MC), [Simrun]=number of simulations run (NR=not reported and "-" if MC not applied), [CI]=confidence intervals used (if MC used, otherwise "-") [Simstep]=Forecast period (A=annual, M=monthly, D=daily) + Detail (spatial (S)/ agent-based (AB). *In progress = not yet available since study ongoing but reported to be applied.

Auth. & Year	Study purpose	MC/Simrun/ CI/Simstep + Detail
Aransiola et al. 2024	To assess if expanding Social Assistance could reduce infant and child mortality in Brazil.	Yes/10000/Yes/A
Archer et al. 2021	To project the prevalence of chronic diseases and their economic impacts using the Future Elderly Model (FEM) in the UK.	Yes/100/Yes/A
Atella et al. 2021	To project future individual health status across OECD countries by applying several FEM models.	Yes/NR/Yes/A
Baldini et al. 2008	To assess the characteristics of the long-term disabled in Italy and the evolution of public expenditure for long-term care.	Yes/NR/No/A
Ballas et al. 2005	To simulate the basic components of population change in Ireland using spatial SMILE model.	Yes/NR/No/A + S
Ballas et al. 2005	To simulate urban and regional populations in UK.	No/-/-/A + S
Becker et al. 2024	To assess the efficiency of COVID-19 mitigation strategies with the CEACOV model in U.S.	-/-/-/D
Bonin et al. 2015	To model monetary value of family policy measures with ZEW model in Germany.	No/-/-/A
Böheim et al. 2023	To model the impact of health and education on labor force participation in US and Germany.	Yes/12/No/A
Brouwers et al. 2016	To study the effects of an ageing population on inpatient and elderly care with SESIM-LEV model in Sweden.	No/-/-/A
Chen et al. 2019	To model fiscal sustainability of healthcare by projecting the health of future elders using FEM model for Singapore.	No/-/-/A
Craig et al. 2022	To simulate the long-term health impacts in UK.	Yes/10000/Yes, In progress*/A

Table 1: Reviewed studies of DMs. Legend: [MC]=Monte Carlo method used (Yes/No or "-" if unclear and additional NR=not reported, if repeated simulation applied without reporting the method or "B" if bootstrapping is applied instead of MC), [Simrun]=number of simulations run (NR=not reported and "-" if MC not applied), [CI]=confidence intervals used (if MC used, otherwise "-") [Simstep]=Forecast period (A=annual, M=monthly, D=daily) + Detail (spatial (S)/ agent-based (AB). *In progress = not yet available since study ongoing but reported to be applied. (cont.).

Ernst et al. 2023	To analyse migration impacts on demographics in Germany.	Yes/NR/No/ A + S
Flannery & O'Donoghue 2011	To study the fiscal and redistributive impacts of different higher education finance structures using the LIAM model in Ireland.	No/-/-/A
Fukawa 2011	To project health/long-term care expenditures with the INAHSIM-II model in Japan.	Yes/NR/No/ A
Head et al. 2024	To model time individuals spent in different health states in UK.	Yes/100/Yes/ A
Horvath et al. 2023	To project healthcare costs over the lifecycle using microWELT model in Austria.	No/-/-/A
Ben Jelloul et al. 2023	To forecast morbidity of population aged +60 and identify causing factors in France.	No/-/-/A
Jiang & Li 2024	To project the population size and share of late middle-aged/older people with difficulties/dependence on activities of daily living (DL) and instrumental activities of DL with the CHARISMA model in China.	Yes, NR/1000/No/ A
Keegan 2021	To simulate the distributional impact of pension policy scenarios on superannuation savings using the APPSIM model in Australia.	No/-/-/A
Khalil et al. 2024	To predict demographic dynamics in Canada with STELARS model.	No/-/-/A + AB
Kingston et al. 2018	To predict the survival and (risk/disease) characteristics and related health expectancies in UK using PACSim model.	Yes, NR/10/-/A
Kirn &Dekkers 2023	To simulate with MIDAS_CH model the distribution of pension income and its underlying processes in Switzerland.	No/-/-/A
Knoef et al. 2013	To analyse the income distribution of the Dutch elderly.	Yes/NR/No/ A
Kopasker et al. 2024	To project changes in psychological distress given predicted economic outcomes. from a tax-benefit UKMOD model with SimPaths model in UK.	Yes, NR/1000/Yes /A
Lawson 2016	To model how demographic change is likely to affect household spending patterns in the UK.	Yes/5/Yes/A
Li et al. 2024	To model the spread of COVID-1 in China.	Yes, NR/10/Yes/D + S, AB
Maitino et al. 2020	To study the future socio-demographic structure and the effects of social security programmes in Italy.	Yes/NR/No/ A + S
Marois & Aktas 2021	To project the health of cohorts for selected EU countries to study the effects of risk factors and education on future health trajectories using ATHLOS-Mic model.	Yes/NR/No/ A
May et al. 2022	To project the health and service use among elderly in Ireland using TILDA model.	Yes/25/No/A
Milne et al. 2016	To model child development from birth to age 13 with MELC model and studying e.g., changes in family circumstances and early education in New Zealand.	Yes, NR/10/Yes/A
Nadeau et al. 2013	To model physical activity to inform population health policies using POHEM-PA model in Canada.	Yes, B/40/Yes/An nual
Patxot et al. 2018	To model the impact of retirement decision and demographics on pension sustainability in Spain.	-/-/-/A
Rasella et al. 2021	To analyse the prospective effects of fiscal policies on childhood health in the EU countries and in Italy.	Yes/1000/Ye s/A
Rephann & Holm 2004	To model economic-demographic effects of immigration in Sweden using the SVERIGE model.	Yes/NR/No/ A + S
Spielauer & Dupriez 2019	To model a variety of demographic and health characteristics with DYNAMIS-POP model in Canada.	Yes/NR/No/ A
Spooner et al. 2021	To model epidemics with spatial SPENSER model in UK.	Yes, NR/1000/Yes /D + S
Tamborini et al. 2022	To analyze socioeconomic gaps in retirement benefits using the MINT model in U.S.	No/-/-/M, A
Tikanmäki et al. 2015	To analyse impacts of the pension reform on working lives using ELSI model in Finland.	Yes/NR/No/ A
van Sonsbeek & Gradus 2005	To simulate the budgetary impact of the 2006 regime change in the Dutch disability scheme.	Yes/NR/No/ A
Walker 2004	To model the likelihood that more Australians aged 65-70 will work +15 hours per week in a changing employment environment.	Yes/NR/No/ A
Wu et al. 2011	To model several demographic processes under various scenarios with a Moses in UK.	Yes/NR/No/ A + S, AB
Zhang & Miller 2024	To predict the location of new housing supply in U.S.	No/-/-/- + S, AB
Zhang et al. 2023	To model the processes of developing depression and care-seeking behaviors among U.S children and adolescents.	Yes, NR/20/Yes/ M

studies reported using 10 000 and four studies 1000 simulation runs. In the remainder, the number of simulations vary from five to forty.

Additionally, there is a notable variability in depth across publications about the discussion of the sources and mitigation of uncertainty. Many studies indirectly or directly, but briefly, address uncertainty when discussing issues like data availability and sample size (see e.g., Becker et al., 2024; Kirn and Dekkers, 2023; Rephann & Holm, 2004) or mention it broadly as parameter/statistical/MC uncertainty. Also, authors commonly discuss of "model error" or “model-based bias”, which intersects with the uncertainty concept (see e.g., Atella et al., 2021; Jiang et al., 2021; Knoef et al., 2013; Kopasker et al., 2024; Lawson, 2016; Marois & Aktas, 2021; Spielauer & Dupriez, 2019).

Focusing on data aspects in terms of data timeliness, only three pandemic-related models and two exceptions from other disciplines seems to offer sub-annual observation periods in models, reaching daily or monthly level accuracy in simulation results. To mention, in their multi-morbidity modeling study, although simulation results are presented in yearly interval, Kingston et al. (2018) updated individual’s characteristics monthly over the simulation time period “to achieve a more realistic evolution for characteristics which jointly influence each other”, similarly than Böheim et al. (2023) regarding labour force status.

Also, to the best of our understanding, only epidemiology models by Becker et al. (2024) and Spooner et al. (2024) target to produce forecasts using near-real-time data with updates. In rest of the models, it seems common to use administrative statistics with a time lag of at least 2-3 years in model initialization.

Lastly, nine studies reviewed are by their nature spatial, including epidemiology studies. Four studies combined the ABM method with DMs, three of them being also spatial (see again Table 1).

2.2 Results Analysis

2.2.1 Uncertainty Analysis

The literature covered indicates varying practices in the application of the MC method and related reporting, highlighting a need for common standards and/or strategies to improve the transparency and comparability of demographic models in the research field. This will not only improve the accuracy of individual studies but also facilitate more robust analyses and comparisons across different research efforts in demographic modeling. We justify this claim by the often inadequate depth of the discussion (and missing information) of MC related details, such as the number of simulation rounds (and reasons that led to the number) and lack of CIs. The lack in reporting CIs aligns also with Smithson (2003), who noticed that different disciplines vary considerably how frequently they report CIs in published research (see also Lappo, 2015; O’Donoghue 2014, 332; O’Donoghue & Dekkers, 2018). Kingston et al. (2018) notes the lack of CIs as one of their study limitations, although the authors also highlight that running the simulation iteratively reveals a small range of prevalence for multi-morbidity (less than 1 %), even when the error in transition rates is disregarded. Knoef et al. (2013) reported not using CIs due the “computational reasons”. Lappo (2015), however, states that the omission of reporting CIs may be since many microsimulation users are not statisticians, perhaps so be in the case of social sciences. However, this indicates a prevalent lack of established practices in employing methods to convey information on result variability across study disciplines (see e.g., Li & O’Donoghue, 2013).

To further explore practices related to the MC method, some authors provide the basis (or tests made) for selecting the number of simulations such as Rasella et al. (2021), who state that a thousand simulation runs was chosen after ensuring that the estimates were stable and additional runs did not alter the point estimates (see also Van Sonsbeek & Gradus, 2005). Spielauer and Dupriez (2019) claimed that 24 iterations make MC variation neglectable, whereas Aransiola et al. (2024) performed 10k rounds to ensure the variation of the parameter values. Overall, the selection of the number of MC simulation runs has received only limited attention even though it is a crucial factor for generating meaningful predictions (see e.g., Byrne 2013; Kennedy 2019, Kennedy et al. 2000). There is a position to analyze more comprehensively the specific factors contributing to the large variation in the number of simulations, especially within studies investigating the same phenomena and “sharing” the same uncertainty elements. Overall, we can concur with O’Donoghue and Dekkers (2018) who noted that alignment techniques (not a focus of this study) are so common in DMs that most reports do not even mention them, despite their significant impact on simulation results. This oversight is similar to the treatment of the MC method (see also Byrne, 2013; Lorscheid et al., 2012; Kennedy, 2019).

When analyzing the overall use of the MC approach, studies reveal differing perspectives on the objectives of modeling: some prioritize analyzing current systems without accounting for variations or forecasting goals, thus considering repeated simulations unnecessary (see e.g., Ben Jelloul et al., 2023; Flannery & O'Donoghue, 2011). In contrast, the majority (30 out of 44) employ the probabilistic method to understand system functionality under uncertainty. Studies focusing on individual behavior and future trends through predefined scenarios and single-point estimates may fail to capture the full spectrum of potential outcomes or convey the inherent uncertainty of modeled phenomena. Such approaches might overlook rare yet impactful events, whereas the MC accounts for these events and their potential consequences (see Fuchs et al., 2018; Gilbert et al., 2018; Marois & Aktas, 2021; O'Donoghue, 2014; Rutter et al., 2011).

2.2.2 Data Granularity and Timeliness

Considering data aspects, the shortcomings of the models running yearly intervals have been recognized. Salonen et al. (2021) highlight challenges in capturing gradual changes such as increase in pension age or short social security spells with a model allowing transitions in one year time intervals. For instance, based on data, the average duration of sickness and unemployment spells is one week, although these periods accumulate over an individual's life course (see also Perhoniemi et al., 2023; Zaidi and Rake, 2001). Although Kingston et al. (2018) provides forecasts in yearly intervals, they enhanced the accuracy of their simulation results by updating health behaviors and disease conditions on a monthly basis. Chen et al. (2019) acknowledges the limitation of not modeling shorter disease dynamics similarly than Andreassen et al. (2020), who suggest that with improved data access and today's computing power, monthly time units could be preferable in the MOSART model (renowned for evaluating the Norwegian pension system) to avoid aggregating data annually and potentially overlooking nuances.

To continue, in an ideal world, employing close-to-real time data for model calibration would reduce the risk of obsolete information affecting transition probabilities – an issue that is especially important when addressing rapidly evolving matters, such as changes in labour market status during economic crisis (see e.g., O'Donoghue & Sologon, 2023). To the best of understanding, no research efforts in this direction were found in this review except epidemiology models. The findings align also with O'Donoghue and Loughrey (2014), who observed that microsimulation models tend to be built on historical data (see also Klevmarken, 2008), limiting researchers' ability to analyze and monitor recent changes and developments.

However, it's important to note that not many phenomena require the daily/monthly forecast accuracy and frequent data calibration typical in pandemic research. Instead, "traditional" social policy models could aim to reduce the delay between data collection and utilization, moving from a lag of several years to using more recent statistics. This shift would better reflect contemporary issues, such as the interconnections between labour force participation and health status (see O'Donoghue & Sologon, 2023).

Admittedly, increased granularity and the use of more timely data to update transition probabilities (together with MC method) add to model complexity in regards of model calibration and computational demands. Nevertheless, many renowned models in the field already require substantial computing power and resources for maintenance due to their high modularity. Today's technological capabilities, such as cloud computing and big data analytics can help overcoming this issue (see Andreassen et al., 2020; O'Donoghue & Dekkers, 2018; Richiardi et al., 2023).

Looking forward, there may be a trend towards simpler models that allow for agile calibration with detailed, current data, albeit sacrificing some modularity (Harding, 2007; Li & O'Donoghue, 2013; Zaidi & Rake, 2001). For instance, localized projections (with ABM approach) are vital for addressing regional disparities and tailoring policies to specific areas. They enhance the relevance of simulations and allow for more detailed evaluations of policy impacts (see Ballas et al., 2005; Birkin et al., 2017; Ernst et al., 2023; Wu & Birkin, 2011). Agile calibrated models providing timely forecasts could potentially be recognized also at the tactical decision-making level.

2.2.3 Other Findings

Machine learning (ML) techniques, in addition to being utilized in model calibration tasks, can aid in addressing complexity arising from models' non-linearities, a topic of ongoing discussion (see e.g., Jiang & Li, 2024; Klevmarken, 2008; Kopasker et al., 2024; O'Donoghue & Dekkers, 2018; Wolfson & Rowe, 2014). The integration of ML could enable the development of more dynamic and predictive models, which could better address complex societal challenges and facilitate faster decision-making. These methods could uncover unobserved, detailed behavioural patterns among individuals thus improving simulation granularity and supporting e.g., ABM constructions (see discussion of Margetts & Dorobatu, 2023). That is, model structures where individual model components interact with each other instead of being passive and detached (see e.g., Axtell 2000). Although there are few applications within the reviewed works, Khalil et al. (2024) provide an innovative application of explainable artificial intelligence (xAI) with the aim to interpret ML models, elucidating input-output relationships in complex settings. This study can be regarded as a pioneering effort in integrating ML within DM schemes in the research domain. Other studies like Rodriguez et al. (2022) in healthcare and other ML-assisted models (see e.g., Shi et al., 2015) offer also insights into applying advanced methods, potentially inspiring social science research.

3 CONCLUSION

This paper presented a literature analysis on the use of probabilistic methods such as Monte Carlo simulation in dynamic microsimulation models and related reporting practices of probabilistic outcomes. This study, to the best of our knowledge, is the first review that addresses the use of such methods and related challenges in reporting the analysis findings in the given context.

It was shown that the current literature often lacks a statistical treatment of the model and if given, there are no standard practices on how a (MC) simulation is conducted and presented. As another important finding, we did not find evidence that attempts were made to develop DMs towards nowcasting with the help of extensive real-time datasets in other study contexts than epidemiology.

The results imply that population-based modeling studies, a predominant focus of the review conducted, could adopt probabilistic thinking to address the inherent uncertainty associated with complex socio-economic processes to make the modeling results more robust and reliable. Common guidelines for UA application and related communication/reporting practices could enhance the transparency of modeling insights as the vulnerability of results would become better communicated to policymakers and less weight could be put on single-point estimates. Also, transition probabilities calculated sub-annual periods can lead to more accurate simulations by incorporating finer temporal variations, e.g., monthly updates can capture short-term trends or immediate impacts of policy changes that yearly intervals might miss. In this regard, it was concluded that the research field could benefit from the development and application of smaller, more targeted models that could offer greater agility in terms of maintenance, particularly in incorporating updated data.

This paper has limitations, notably not being a fully comprehensive systematic review. Nonetheless, it provides some preliminary directions for future research efforts to improve probabilistic treatment of DMs in the context of demographic models. Additionally, future research could assess the role of emerging technologies, such as cloud computing, machine learning techniques, and big data analytics.

The final limitation of this research to be pointed out is the method used to assess data granularity, categorizing models as agent-based or spatial. Future evaluations could provide an extended analysis of variables like demographic precision. A more comprehensive review could delve deeper into whether the nature of the phenomena being modeled warrants more frequent updates to transition probabilities. The review focused only on the MC method with frequentist viewpoint, omitting Bayesian methods or distinguishing bootstrapping from MC approach. It also did not cover the alignment techniques used together with the MC, or other reporting practices such as goodness-of-fit or standard error statistics.

REFERENCES

Alho, J., & Lassila, J. (2023). Assessing components of uncertainty in demographic forecasts with an application to fiscal sustainability. Journal of Forecasting, 42(7), 1560-1568.

Andreassen, L., Fredriksen, D., Gjefsen, H. M., Halvorsen, E., & Stølen, N. M. (2020). The dynamic cross-sectional microsimulation model MOSART. International Journal of Microsimulation, 13(1), 92-113.

Aransiola, T. J., Cavalcanti, D., Ordoñez, J. A., Hessel, P., Moncayo, A. L., Chivardi, C., ... & Rasella, D. (2024). Current and Projected Mortality and Hospitalization Rates Associated With Conditional Cash Transfer, Social Pension, and Primary Health Care Programs in Brazil, 2000-2030. JAMA Network Open, 7(4), e247519-e247519.

Archer, L., Lomax, N., & Tysinger, B. (2021). A dynamic microsimulation model for ageing and health in england: The english future elderly model. International Journal of Microsimulation, 14(3), 2-26.

Astolfi, R., Lorenzoni, L., & Oderkirk, J. (2012). Informing policy makers about future health spending: a comparative analysis of forecasting methods in OECD countries. Health Policy, 107(1), 1-10.

Atella, V., Belotti, F., Kim, D., Goldman, D., Gracner, T., Piano Mortari, A., & Tysinger, B. (2021). The future of the elderly population health status: Filling a knowledge gap. Health economics, 30, 11-29.

Axtell, R. (2000). Why agents?: on the varied motivations for agent computing in the social sciences (Vol. 17). Washington, DC: Center on Social and Economic Dynamics.

Ballas, D., Clarke, G., Dorling, D., Eyre, H., Thomas, B., & Rossiter, D. (2005). SimBritain: a spatial microsimulation approach to population dynamics. Population, Space and Place, 11(1), 13-34.

Ballas, D., Clarke, G. P., & Wiemers, E. (2005). Building a dynamic spatial microsimulation model for Ireland. Population, Space and Place, 11(3), 157-172.

Becker, J. E., Shebl, F. M., Losina, E., Wilson, A., Levison, J. H., Donelan, K., ... & Freedberg, K. A. (2024). Using simulation modeling to inform intervention and implementation selection in a rapid stakeholder-engaged hybrid effectiveness-implementation randomized trial. Implementation Science Communications, 5(1), 70.

Ben Jelloul, M., Bozio, A., Perdrix, E., Rain, A., & Toulemon, L. (2023). Dynamique du processus de perte d'autonomie dans les populations vieillissantes/Dynamic of the Disablement Process in Ageing Populations. Economie et Statistique, 538(1), 13-31.

Birkin, M., Wu, B., & Rees, P. (2017). Moses: dynamic spatial microsimulation with demographic interactions. New frontiers in microsimulation modelling, 53-77.

Bonin, H., Reuss, K., & Stichnoth, H. (2015). Life-cycle incidence of family policy measures in Germany: Evidence from a dynamic microsimulation model.

Brown, L., & Harding, A. (2002). Social modelling and public policy: Application of microsimulation modelling in Australia. Journal of Artificial Societies and Social Simulation, 5(4).

Burka, D., Mohácsi, L., Csicsman, J., & Soós, B. (2017). Supporting Pension Pre-Calculation With Dynamic Microsimulation Technologies. In ECMS (pp. 562-568).

Burgard, J. P., & Schmaus, S. (2019). Sensitivity analysis for dynamic microsimulation models (No. 15/19). Research Papers in Economics.

Burgard, J. P., Krause, J., Merkle, H., Münnich, R., & Schmaus, S. (2019). Conducting a dynamic microsimulation for care research: Data generation, transition probabilities and sensitivity analysis. In Stochastic Models, Statistics and Their Applications: Dresden, Germany, March 2019 14 (pp. 269-290). Springer International Publishing.

Burgard, J. P., Krause, J., & Schmaus, S. (2021). Estimation of regional transition probabilities for spatial dynamic microsimulations from survey data lacking in regional detail. Computational Statistics & Data Analysis, 154, 107048.

Byrne, M. D. (2013). How many times should a stochastic model be run? An approach based on confidence intervals. In Proceedings of the 12th International conference on cognitive modeling, Ottawa.

Böheim, R., Horvath, T., Leoni, T., & Spielauer, M. (2023). The Impact of Health and Education on Labor Force Participation in Aging Societies: Projections for the United States and Germany from Dynamic Microsimulations. Population Research and Policy Review, 42(3), 39. Simulation, 21(1).

Caro, J. J., Briggs, A. H., Siebert, U., & Kuntz, K. M. (2012). Modeling good research practices—overview: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force–1. Medical Decision Making, 32(5), 667-677.

Chen, C., Lim, J. T., Chia, N. C., Wang, L., Tysinger, B., Zissimopoulos, J., ... & Yoong, J. (2019). The long-term impact of functional disability on hospitalization spending in Singapore. The Journal of the Economics of Ageing, 14, 100193.

Craig, P., Barr, B., Baxter, A. J., Brown, H., Cheetham, M., Gibson, M., ... & Bambra, C. (2022). Evaluation of the mental health impacts of Universal Credit: protocol for a mixed methods study. BMJ open, 12(4), e061340.

Crato, N. (2023). From lack of data to data unlocking: Computational and statistical issues in an era of unforeseeable big data evolution. In Handbook of Computational Social Science for Policy (pp. 125-139). Cham: Springer International Publishing.

Dekkers, G. (2015). The simulation properties of microsimulation models with static and dynamic ageing–a brief guide into choosing one type of model over the other. International Journal of Microsimulation, 8(1), 97-109.

Ernst, J., Dräger, S., Schmaus, S., Weymeirsch, J., Alsaloum, A., & Münnich, R. (2023). The Influence of Migration Patterns on Regional Demographic Development in Germany. Social Sciences, 12(5), 255.

Flannery, D., & O'Donoghue, C. (2011). The Life-cycle Impact of Alternative Higher Education Finance Systems in Ireland. Economic & Social Review, 42(3).

Fontana, M., & Guerzoni, M. (2022). Modelling Complexity with Unconventional Data: Foundational Issues in Computational Social Science. In Handbook of Computational Social Science for Policy (pp. 107-124). Cham: Springer International Publishing.

Fuchs, J., Söhnlein, D., Weber, B., & Weber, E. (2018). Stochastic forecasting of labor supply and population: An integrated model. Population Research and Policy Review, 37(1), 33-58.

Fukawa, T. (2011). Household projection and its application to health/long-term care expenditures in Japan using INAHSIM-II. Social Science Computer Review, 29(1), 52-66.

Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K. P., & Wilkinson, H. (2018). Computational modelling of public policy: Reflections on practice. Journal of Artificial Societies and Social

Harding, A. (2007, August). Challenges and opportunities of dynamic microsimulation modelling. In Plenary paper presented to the 1st General Conference of the International Microsimulation Association

Head, A., Birkett, M., Fleming, K., Kypridemos, C., & O'Flaherty, M. (2024). Socioeconomic inequalities in accumulation of multimorbidity in England from 2019 to 2049: a microsimulation projection study. The Lancet Public Health, 9(4), e231-e239.

Horvath, T., Leoni, T., Reschenhofer, P., & Spielauer, M. (2023). Socio-economic inequality and healthcare costs over the life course–A dynamic microsimulation approach. Public Health, 219, 124-130.

Jiang, Y., & Li, L. (2024). Projections of functional dependence among the late middle-aged and older population from 2018-2048 in China: a dynamic microsimulation. Global Health Research and Policy, 9(1), 15.

Kashyap, R., & Zagheni, E. (2023). Leveraging Digital and Computational Demography for Policy Insights. In Handbook of Computational Social Science for Policy (pp. 327-344). Cham: Springer International Publishing.

Keegan, M. (2011). Mandatory superannuation and self-sufficiency in retirement: an application of the APPSIM dynamic microsimulation model. Social science computer review, 29(1), 67-84.

Kennedy, M. C. (2019). Experimental design principles to choose the number of Monte Carlo replicates for stochastic ecological models. Ecological Modelling, 394, 11-17.

Khalil, M. A., Fatmi, M. R., & Orvin, M. (2024). Developing and microsimulating demographic dynamics for an integrated urban model: a comparison between logistic regression and machine learning techniques. Transportation, 1-35.

Klevmarken, A. (2008). Chapter 2 Dynamic Microsimulation for Policy Analysis: Problems and Solutions. In Simulating an ageing population: A microsimulation approach applied to Sweden (pp. 31-53). Emerald Group Publishing Limited.

Kingston, A., Robinson, L., Booth, H., Knapp, M., Jagger, C., & Modem Project. (2018). Projections of multi-morbidity in the older population in England to 2035: estimates from the Population Ageing and Care Simulation (PACSim) model. Age and ageing, 47(3), 374-380.

Knoef, M., Alessie, R., & Kalwij, A. (2013). Changes in the Income Distribution of the D utch Elderly between 1989 and 2020: a Dynamic Microsimulation. Review of Income and Wealth, 59(3), 460-485.

Kopasker, D., Bronka, P., Thomson, R. M., Khodygo, V., Kromydas, T., Meier, P., ... & Katikireddi, S. V. (2024). Evaluating the influence of taxation and social security policies on psychological distress: A microsimulation study of the UK during the COVID-19 economic crisis. Social Science & Medicine, 351, 116953.

Lappo, S. (2015). Uncertainty in microsimulation. Master's Thesis, University of Helsinki.

Lawson, T. (2016). How the ageing population contributes to UK economic activity: A microsimulation analysis. Scottish Journal of Political Economy, 63(5), 497-518.

Lee, R. D., & Tuljapurkar, S. (1994). Stochastic population forecasts for the United States: Beyond high, medium, and low. Journal of the American Statistical Association, 89(428), 1175-1189.

Lee, J. T., Crettenden, I., Tran, M., Miller, D., Cormack, M., Cahill, M., ... & Xiang, F. (2024). Methods for health workforce projection model: systematic review and recommended good practice reporting guideline. Human Resources for Health, 22(1), 25.

Lee, R., & Tuljapurkar, S. (1994). Stochastic population forecasts for the United States: Beyond high, medium, and low. Journal of the American Statistical Association, 89(428), 1175–1189.

van Leeuwen, E. (2016). Simulating the expenditures of Scottish households: a two-step microsimulation approach to the Cairngorms National Park. In New Pathways in Microsimulation (pp. 233-248). Routledge.

Li, Z., Xiong, G., Lv, Y., Ye, P., Liu, X., Tarkoma, S., & Wang, F. Y. (2024). An Urban Trajectory Data-Driven Approach for COVID-19 Simulation. IEEE

Li, J., & O'Donoghue, C. (2013). A survey of dynamic microsimulation models: uses, model structure and methodology. International Journal of microsimulation, 6(2), 3-55.

Li, J., & O'Donoghue, C. (2016). An overview of binary alignment methods in microsimulation. New Pathways in Microsimulation, 233-248.

Lorscheid, I., Heine, B. O., & Meyer, M. (2012). Opening the 'black box'of simulations: increased transparency and effective communication through the systematic design of experiments. Computational and Mathematical Organization Theory, 18, 22-62.

Mahadevan, S., & Sarkar, S. (2009). Uncertainty analysis methods. US Department of Energy, Washington, DC, USA.

Margetts, H., & Dorobantu, C. (2023). Computational social science for public policy. In Handbook of Computational Social Science for Policy (pp. 3-18). Cham: Springer International Publishing.

Marois, G., & Aktas, A. (2021). Projecting health-ageing trajectories in Europe using a dynamic microsimulation model. Scientific reports, 11(1), 1785.

May, P., Normand, C., Matthews, S., Kenny, R. A., Romero-Ortuno, R., & Tysinger, B. (2022). Projecting future health and service use among older people in Ireland: an overview of a dynamic microsimulation model in The Irish Longitudinal Study on Ageing (TILDA). HRB Open Research, 5.

Milne, B., Lay Yee, R., McLay, J. M., Pearson, J., Von Randow, M., & Davis, P. (2015). Modelling the Early life-course (MELC): A microsimulation model of child development in New Zealand.

Münnich, R., Schnell, R., Brenzel, H., Dieckmann, H., Dräger, S., Emmenegger, J., ... & Stein, P. (2021). A population based regional Dynamic microsimulation of Germany: the MikroSim model. methods, data, analyses, 15(2), 24.

Nadeau, C., Wong, S. L., Flanagan, W. M., Oderkirk, J., Manuel, D., Wall, R., & Tremblay, M. S. (2013). Development of a population-based microsimulation

model of physical activity in Canada. Health Rep, 24(10), 11-9.
Navicke, J., Rastrigina, O., & Sutherland, H. (2014). Nowcasting indicators of poverty risk in the European Union: A microsimulation approach. Social Indicators Research, 119, 101-119.
O'Donoghue, C. (2001). Dynamic microsimulation: A methodological survey. Brazilian Electronic Journal of Economics, 4(2), 77.
O'Donoghue, C. (Ed.). (2014). Handbook of microsimulation modelling. Emerald Group Publishing.
O'Donoghue, C., & Dekkers, G. (2018). Increasing the impact of dynamic microsimulation modelling. The International Journal of Microsimulation, 11(1), 61-96.
O'Donoghue, C., & Loughrey, J. (2014). Nowcasting in microsimulation models: a methodological survey. Journal of Artificial Societies and Social Simulation, 17(4), 12. Transactions on Computational.
O'Donoghue, C., & Sologon, D. M. (2023). The Transformation of Public Policy Analysis in Times of Crisis-A Microsimulation-Nowcasting Method Using Big Data.
Patxot, C., Solé Juvés, M., Souto Nieves, G., & Spielauer, M. (2018). The impact of the retirement decision and demographics on pension sustainability: A dynamic microsimulation analysis. International Journal of Microsimulation, 2018, vol. 11, num. 2, p. 84-108.
Perhoniemi, R., Blomgren, J., & Laaksonen, M. (2023). Identifying labour market pathways after a 30-day-long sickness absence–a three-year sequence analysis study in Finland. BMC Public Health, 23(1), 1102.
Rasella, D., Richiardi, L., Brachowicz, N., Jara, H. X., Hanson, M., Boccia, D., ... & Pizzi, C. (2021). Developing an integrated microsimulation model for the impact of fiscal policies on child health in Europe: the example of childhood obesity in Italy. BMC medicine, 19, 1-12.
Rephann, T. J., & Holm, E. (2004). Economic-demographic effects of immigration: results from a dynamic spatial microsimulation model. International Regional Science Review, 27(4), 379-410.
Richiardi, M., Bronka, P., van de Ven, J., Kopasker, D., & Katikireddi, S. V. (2023). SimPaths: an open-source microsimulation model for life course analysis. Available at SSRN 4808042.
Rodriguez, P. J., Veenstra, D. L., Heagerty, P. J., Goss, C. H., Ramos, K. J., & Bansal, A. (2022). A Framework for Using Real-World Data and Health Outcomes Modeling to Evaluate Machine Learning–Based Risk Prediction Models. Value in Health, 25(3), 350-358.
Rutter, C. M., Zaslavsky, A. M., & Feuer, E. J. (2011). Dynamic microsimulation models for health outcomes: a review. Medical Decision Making, 31(1), 10-18.
Sabelhaus, J., & Topoleski, J. (2007). Uncertain policy for an uncertain world: The case of social security. Journal of Policy Analysis and Management, 26(3), 507-525.
Salonen, J., Tikanmäki, H., & Lappo, S. (2021). Partition of the Life Course: An Extended Dynamic Microsimulation Analysis.
Sauerbier, T. (2002). UMDBS-a new tool for dynamic microsimulation. Journal of Artificial Societies and Social Simulation, 5(2).
Sharif, B., Wong, H., Anis, A. H., & Kopec, J. A. (2017). A practical ANOVA approach for uncertainty analysis in population-based disease microsimulation models. Value in Health, 20(4), 710-717.
Sharif, B., Kopec, J. A., Wong, H., Fines, P., Sayre, E. C., Liu, R. R., & Wolfson, M. C. (2012). Uncertainty analysis in population-based disease microsimulation models. Epidemiology Research International, 2012(1), 610405.
Shi, Y., Zeng, W., Wang, N., Wang, S., & Huang, Z. (2015). Early warning for human mental sub-health based on fMRI data analysis: an example from a seafarers' resting-data study. Frontiers in psychology, 6, 1030.
Smithson, M. (2003). Confidence intervals (No. 140). Sage.
Spielauer, M. (2007). Dynamic microsimulation of health care demand, health care finance and the economic impact of health behaviours: survey and review. International Journal of Microsimulation, 1(1), 35-53.
Spielauer, M., & Dupriez, O. (2019). A portable dynamic microsimulation model for population, education and health applications in developing countries. International Journal of Microsimulation, 12(3), 6-27.
Spooner, F., Abrams, J. F., Morrissey, K., Shaddick, G., Batty, M., Milton, R., ... & Birkin, M. (2021). A dynamic microsimulation model for epidemics. Social Science & Medicine, 291, 114461.
Tamborini, C. R., Reznik, G. L., Iams, H. M., & Couch, K. A. (2022). The Growing Socioeconomic Gap in Lifetime Social Security Retirement Benefits: Current and Future Retirees. The Journals of Gerontology: Series B, 77(4), 803-814.
Tikanmäki, H., Sihvonen, H., & Salonen, J. (2015). Distributional Effects of the Forthcoming Finnish Pension Reform: a Dynamic Microsimulation Approach.
Van Sonsbeek, J. M., & Gradus, R. H. (2006). A microsimulation analysis of the 2006 regime change in the Dutch disability scheme. Economic modelling, 23(3), 427-456.
Walker, A. (2004). Impact of health on the ability of older Australians to stay in the workforce-with possible contributions to economic sustainability.
Wolfson, M., & Rowe, G. (2014). HealthPaths: Using functional health trajectories to quantify the relative importance of selected health determinants. Demographic Research, 31, 941-974.
Wu, B. M., Birkin, M. H., & Rees, P. H. (2011). A dynamic MSM with agent elements for spatial demographic forecasting. Social Science Computer Review, 29(1), 145-160.
Xue, X., Chen, F., Zhou, D., Wang, X., Lu, M., & Wang, F. Y. (2021). Computational experiments for complex social systems—Part I: The customization of computational model. IEEE Transactions on Computational Social Systems, 9(5), 1330-1344.

Zaidi, A., & Rake, K. (2001). Dynamic microsimulation models: a review and some lessons for SAGE. Simulating Social Policy in an Ageing Society (SAGE) discussion paper, 2.
Zhang, Y., & Miller, E. J. (2024). Analyzing housing supply location choice: a comparative study of the modelling frameworks. Scientific Reports, 14(1), 1435.
Zhang, C., Zafari, Z., Slejko, J. F., Camelo Castillo, W., Reeves, G. M., & Dosreis, S. (2023). Impact of different interventions on preventing suicide and suicide attempt among children and adolescents in the United States: a microsimulation model study. Frontiers in psychiatry, 14, 1127852.
Zhao, Y., Jiang, C., Vega, M. A., Todd, M. D., & Hu, Z. (2023). Surrogate modeling of nonlinear dynamic systems: a comparative study. Journal of Computing and Information Science in Engineering, 23(1), 011001.