Proceedings of the 2014 Winter Simulation Conference
A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, eds.

DISCRETE CHOICE, AGENT BASED AND SYSTEM DYNAMICS SIMULATION OF HEALTH PROFESSION CAREER PATHS

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ABSTRACT

Modelling real workforce choices accurately via Agent Based Models and System Dynamics requires input data on the actual preferences of individual agents. Often lack of data means that analysts can have an understanding of how agents move through the system, but not why, and when. Hybrid models incorporating discrete choice experiments (DCE) solve this. Unlike simplistic neoclassical economic models, DCEs build on 50 years of well-tested consumer theory that decomposes the utility (benefit) derived from the agent's preferred choice into that associated with its constituent parts, but also allows agents different degrees of certainty in their discrete choices (heteroscedasticity on the latent scale). We use DCE data in populating a System Dynamics/Agent Based Model – one of choices of optometrists and their employers. It shows that low overall predictive power conceals heterogeneity in agents' preferences. Incorporating such preferences in our hybrid approach improves the model's explanatory power and accuracy.

1 INTRODUCTION

The health workforce is a system subjected to a wide range of influences that encompass society as a whole (Masnick and McDonnell 2010). In attempting to realistically understand the complete workforce and the interactions within, it is necessary to limit the variables under consideration, work with partial data and to constrain the methodology. Ono et al. (Ono, Lafortune, and Schoenstein 2013) examined the workforce projections models of OECD countries. No study adequately accounted for individual practitioner behaviors, most were not fully integrated with the aims of the health system itself and many

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were not based on whole-of-career studies. Another study (CHERE 2012) which focused on nurse choices and retention considered the demand side of the health system. System dynamics models(Masnick 2009, Vanderby et al. 2013) have been created to describe the professional health workforce using population supply and demand and student throughput but not at the individual level. The aim of the current study is to integrate three complementary methodologies (System Dynamics (SD), Agent Based Modelling (AB) and Discrete Choice Experiments (DCE)) in order to develop and implement a health professional workforce model that includes an individual's key career decisions within an overall system. Using individual choice data from DCE, the model will provide an aggregate system dynamics picture of workforce stocks and flows and characterize the interplays of agent based spatial distribution of employer jobs, professional supply and population demands. Our experience thus far suggests that the benefits conferred by combining the three intertwining methodologies will be greater than the sum of the benefits applying the individual methodologies in isolation. This paper is an outline of the underlying principles and methodologies being used in this long-term project and a description of an initial proof of concept experiment.

1.1 Background

The authors were asked to investigate a particular set of student problems by a university which trains optometrists. It soon became apparent that those problems were grounded in an overall whole-of–career system in an ever-changing world. We also realized that it would be possible to generalize our work to cover most if not all health professions. Rather than a simple linear flow from high school student to trainee to worker to retirement, there was a need to account for how externalities impact on the workforce as a whole and on each individual within the workforce by building geographic and temporal dynamics and feedbacks into quantifiable models. The conceptual outline can be seen in Figure 1 and Figure 2 (an expanded view is available in Masnick 2014).

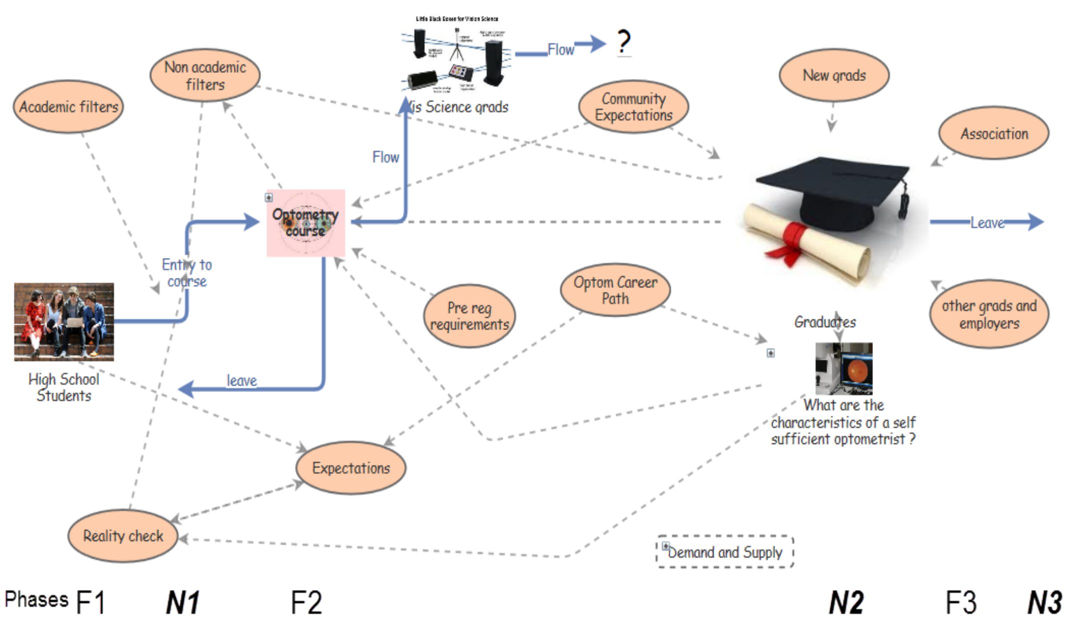

Figure 1. Conceptual picture of the project.

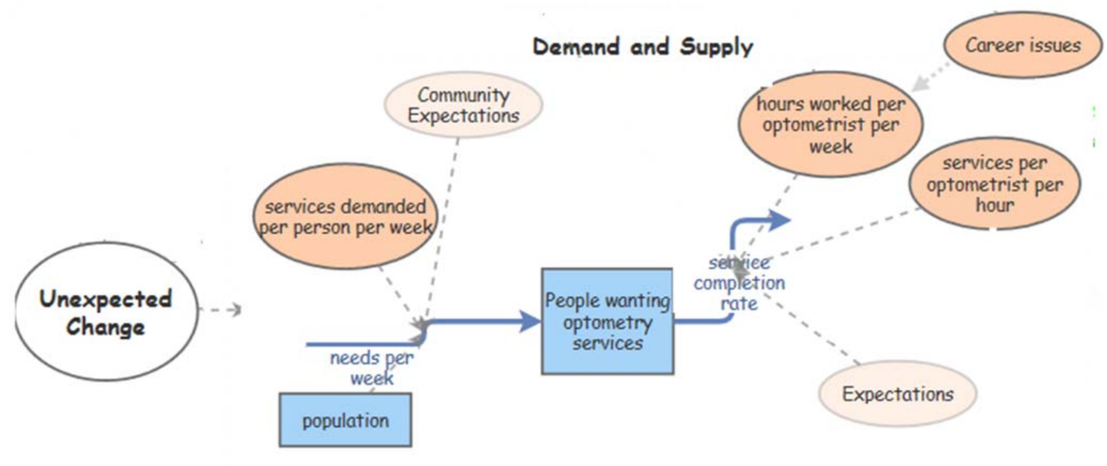

Figure 2. Demand and supply for optometrist's services.

A model is only as good as the methodologies used to inform it and we could find no unique methodology to cover our objectives. We therefore proposed to integrate three different approaches, system dynamics, agent based modelling and discrete choice experiments based on random utility theory (RUT) into a more robust model than any one methodology could provide.

We identified three points (nodes labelled as phases Nx in Figure 1) where there are sharp career changes and three flows between the nodes. Each flow has its own set of issues in addition to the overall systemic one. During Flow 1, potential candidates gather information on their choice of profession and establish a set of expectations and capacities. Node 1 represents the point of decision to enter training. Flow 2 represents learning and matching dynamically modified expectations with the realities of training, represented by retention and achievement parameters. Node 2 is where students finish their course and enter the profession. Flow 3 covers professional life. Node 3 is when professionals finally leave the profession through retirement, change of interest etc. Overall, we seek to investigate education, employment, lived experience (e.g., general work/life balance, family life phases, spatial location of residence and work [especially rural vs. metro], entry/re-entry into work), professional competency and behaviors, awareness of commercial realities (e.g., marketing, promotion of self and organization).

Node 2 (the interface with Flow 3) is the initial focus point of our model. This is where new graduates infer that jobs are in line with their expectations of employment, employers often claim that new graduates do not possess the necessary competencies required for employment and there are issues relating to employment such as style, location, remuneration and career paths which require resolution. The initial planning hybrid methodology (especially SD and ABM) model provides a framework for the later choice modelling part of the project. Once this core is defined, recruitment and training can be appropriately modified and systemic supply and demand can be addressed.

The chosen profession to study was optometry as it is practiced in one state of Australia (New South Wales, population 7M). Optometry is a homogenous profession and good data are available from the profession itself and in its capacity as a component of the National Health Service. The selected state contains the whole range of modes and locations of practice at level that can be subjected to useful analysis.

2 METHODS

The next section of this article is an overview of the three methodologies being used. The subsequent section describes the first study of this project, a discrete choice experiment to quantify values to be assessed.

2.1 Review of Methodologies

Dynamic systemic perspectives have been linked to structure agency theory, where agent actions are constrained and enabled by system structures, including social institutions at the individual, family, peer group, community and other cultural levels (Lane and Husemann 2008). System dynamics is one formal computational dynamic modelling method where the system is represented as stocks, flows and endogenous feedback loops to account for how systems change over time, including accumulations, delays and non-linear interactions (Sterman 2000, Forrester 1968). In the field of human resources for health, SD has been used extensively, with recent examples(Ghaffarzadegan, Hawley, and Desai 2014, Vanderby et al. 2013).

In contrast to SD, which conceptualizes system structure from the "top down", ABM works from the "bottom up" focusing on the characteristics, interactions, and dynamics of many individuals (known as agents) belonging to a larger population (Grimm 2005). Agent-based models are often difficult to capture mathematically (Axtell et al. 2002) and thus simulation of agent-based models is often the only viable way to study populations of adaptive agents (Axelrod 1997). Agent-based modelling offered a strong fit for the current project due to its crisply and scalable capturing of heterogeneity, individual preferences and decision making (Bruch and Mare 2006), multi-level context, and capacity to capture – and individual, institutional decision making to take into account – longitudinal trajectories of individuals.

One body of behavioral economics / psychology that focuses on individual choices is DCE, which uses random utility theory (RUT) to analyze stated preferences based on underlying features of products and services. Joining the two approaches together, we can explore the feasibility and usefulness of linking individual choice behaviors to workforce supply and demand dynamics. We explicitly construct narrative process models that play out on a regional stage over space and time. Based on previous multi-scale work by the authors and others in hospital infection control (Sadsad 2012) we represent different abstractions of scope and level of detail and their complex inter-level interactions. We then design and test some virtual experiments capturing the context mechanism and outcomes of interventions at the policy services and individual choice levels, linking this to regional health system performance.

2.2 Discrete Choice Experiments and Random Utility Theory

Random utility theory (RUT) was proposed by Thurstone (1927) as a way to place items (ranging from simple to multi-dimensional products) on a common underlying latent scale ("utility") quantifying their attractiveness. The model essentially incorporated two key assumptions:

1. Humans are not perfectly consistent when making the same (or similar) choices on repeat occasions
2. The frequency of choosing (for instance) A over B will increase the further apart A and B lie on the latent utility scale.

This "signal to noise" model allows the researcher to infer the positions of all items under consideration on an interval or ratio scale by noting how often each is chosen over another: how often the subject chooses A over B quantifies how much the subject values A over B. Advantages of this approach include the fact the respondents are not asked for numbers to indicate the attractiveness of items. It has long been observed, and more recently established (Steenkamp and Baumgartner 1998, Baumgartner and Steenkamp 2001), that people are not consistent in how they use numerical scales. The metric here is a probability scale (observed frequencies) with known mathematical properties (ratio or interval depending on the transformation used).

Thurstone was unable to generalize the model beyond paired comparisons due to his use of normal distributions (with no closed form solution for multinomial choices). In the 1950s and 1960s mathematical psychologists Luce and Marley (in Luce and Suppes 1965) (amongst others) solved Thurstone's problem, extending the choice framework to one containing three or more objects through use of the logistic model. The "Luce model", and its re-parameterization as a multinomial logistic regression model (MNL), was the result. Independently of this, McFadden (McFadden 1974) working in economics, established the properties of the MNL model, which proved more tractable by working with estimates of the utilities on the (interval) scale produced by applying the logistic transformation to the probabilities, rather than the probabilities themselves. Implementing RUT fully required developments in computing to estimate the logit models, statistical design sets to understand how many and what composition of "choice" were presented to people to obtain stable frequency estimates and an understanding of how respondents might combine the utilities of the constituent parts of a multi-dimensional good to calculate a total value score in order to make a decision.

Logit models typically serve as the link function between observed frequencies (probabilities) and underlying quantities on the latent (interval) scale. Manski (1977) established that the value (utility) derived from a multi-attribute (multidimensional) good could be represented by some weighted sum of those derived from its parts. Louviere and Hensher (together with George Woodworth) drew on the "conjoint" analysis literature to provide simple designs that allowed this process to be "reversed" (Louviere and Woodworth 1983, Louviere and Hensher 1982): to decompose the total value derived from a good into the values associated with its constituent parts.

Bayesian designs using priors (ideally from pilot studies) have aided researchers in presenting the "right" choice sets – i.e. those that are most informative in eliciting the individual's utility function. Two psychological models, the G-MNL (Fiebig et al. 2010) and scale adjusted latent class model (Flynn et al. 2010) have helped in modelling differences in how consistent respondents really are in response to common stimuli (choice sets). Thus, the nesting of DCEs within wider models that incorporate real population decisions, as is proposed in this project, will provide an excellent solution to the problem.

2.3 The DCE Design

As noted earlier, the focus of the study proposed here concerns Node 2: in particular, what are the features (attributes) of a newly qualified optometrist that are valued by potential employers and how much do they value these? Limited resources and sample size mean the model functional form (decision model type) is assumed to be additive: the utility derived by an employer from a given "type" of newly qualified optometrist is a simple weighted sum of the attributes of that type. An employer is assumed to derive utility from the attributes of a type of optometry graduate; different amounts ("levels") of each attribute (for example, levels of reservation wage, stated willingness to relocate) provide different utilities to the employer. The weights applied to these are derived from the DCE from observing the choices that a sample of employers make between competing types of graduate.

The number of attributes and levels is to be kept sufficiently small that a main effects plan requires only a manageable number of choice sets (decisions; typically up to 32 but often around 20). Ideally, the number of parameters to be estimated will be less than the number of choice sets: in that case, the number of degrees of freedom at the level of the individual decision-maker will be positive, allowing the estimation of a decision rule for every individual, without the need to make assumptions concerning distributions of preferences. This will be particularly important here, where only a small sample of employers is likely to be recruited. The content of the paper should be objective and without any appearance of commercialism. In general, comparisons of commercial software should be avoided unless they are central to the topic. If a comparison of commercial software is included, it should be based on objective analysis that includes criteria, description of ranking methodology on each criteria, and the rankings themselves to arrive at the conclusion. If an approach other than a detailed objective analysis is used to select the simulation software used for the study being reported, such as, availability of the software, or the familiarity of the analyst with the software, it should be clearly identified.

3 HYBRID DYNAMIC MODELING

Our hybrid dynamic model integrates both Agent-Based and System Dynamics elements. The model is implemented using AnyLogic (AnyLogic 2014), a modelling framework that integrates support for SD, ABM, and other dynamic modelling techniques. AnyLogic has a rich state-chart library that allows for our representation of agent decisions. AnyLogic uses either continuous or discrete event time at the user's choice; our model utilizes discrete time to simplify the conceptual understanding of how decisions are performed. We employ a standard protocol (Grimm et al. 2006) to describe our hybrid model which the DCE will feed probabilistic calibration data in conjunction with ABM.

3.1 Purpose

In general, hybrid models are capable of explicitly linking data and theory at multiple levels of abstraction in order to explore, test and refine causal inferences in complex systems. Our focus is to explicitly link the aggregate view of health policy makers and the individual views of health professionals, patients and their caregivers. The assumptions about aggregation can be made explicit and therefore able to experimented with in the model. This approach promises to provide effective decision support to align decisions at the strategic population policy and individual clinical level.

This particular hybrid model intends to incorporate individual-based optometrist' key career decisions in their career life combined with population-level estimates of demand for optometrists in Australia. The ultimate purpose is to explore whether we are able to adequately predict trends and changes in the Australian optometry profession by modelling choice processes at an individual level. Beyond the implications for the optometry profession as a whole, we are further interested in determining what factors dominate certain decisions that optometrists make.

3.2 State Variables and Scales

The model comprises three hierarchical levels: optometrist, Australian States, (meta) population. Optometrists (Agent) are characterized by their social-demographic variables (seen in Figure 3): identity number, age, gender, identity of the Australian state where the optometrist lives and works (including rural or metro), birth region, and professional standing – such as whether they are in school or their status in the workforce – and marital and parental status, such as if they are single, married, or pregnant. There are additional variables representing preferences related to the decisions they make, and measures of optometrists' professional proficiency and social skills.

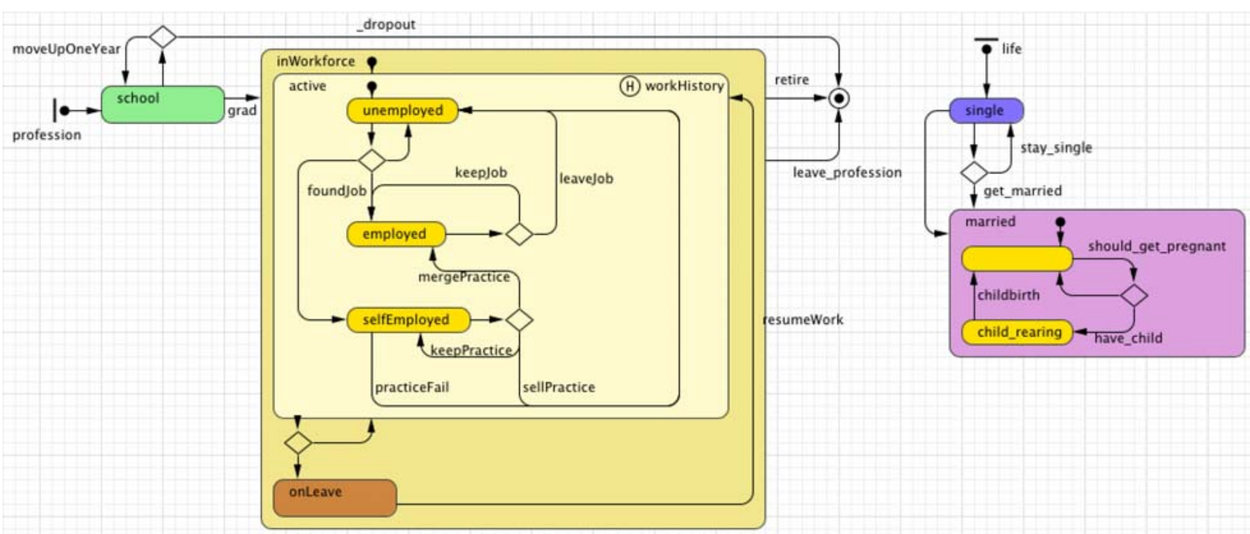

Figure 3. Optometrist's life state charts.

Each Australian State (Agent) has a dynamic population, a list of optometrists that are working or schooling in the State, and a listing of currently occupied or opened optometrist employment positions. The population dynamics embedded in each State are captured using a simplistic SD model (Figure 4). The SD model in each State provide crude estimates for the demand for optometrists. On the supply side, the existing the optometrists in the corresponding State interact with State about opened employment position periodically. The model representation of State job market dynamics is currently highly stylized. That is, employers or government needs are not explicitly represented within State regions; jobs are simply created according to the size of the population and are generated with random attributes, such as qualifications and pay scale.

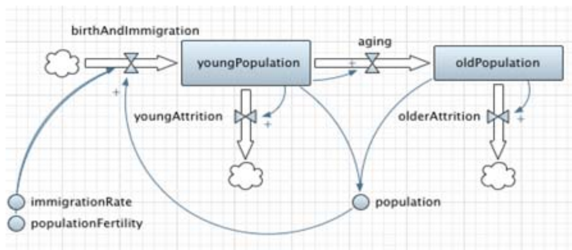

Figure 4. Population dynamics per Australian state.

The population is composed of seven Australian States. Population are characterized by population size, the number of overall optometrists, and the number of candidate optometrists in school, the number of overall jobs. The geographical location of the States are incorporated (Figure 5), and further GIS integration and incorporation of spatial context could be easily implemented given support from ABM in general and the AnyLogic package in particular.

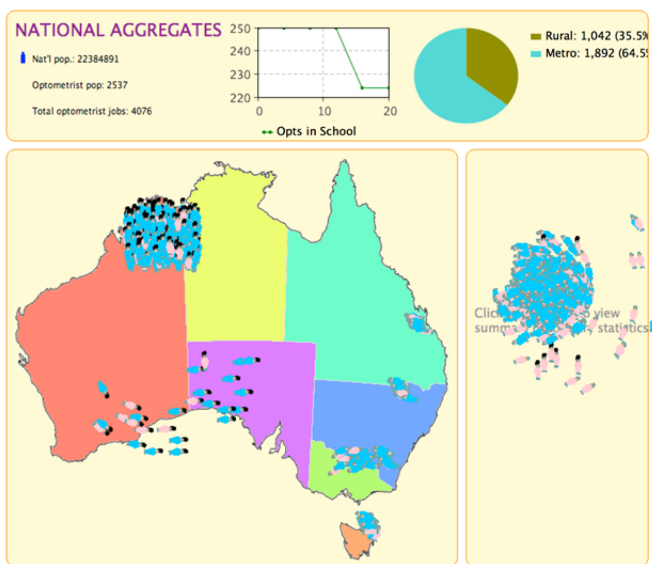

Figure 5. Spatial arrangement of Australian States in the model.

The model does not currently consider an agent's location beyond the need to associate population, optometrist agents, and jobs with regions. There is no concept of "distance" within the model.

3.3 Process Overview and Scheduling

While a continuous-time abstraction based on calendar time is employed, model time and events for the ABM and the System Dynamics model operate at a discrete level. That is, events are evaluated in discrete time and events of a particular type (e.g., calculating aggregate statistics) are evaluated all at once (such as at the end of a year). The ABM's temporal resolution is approximately a week. The current model's start time is January 1st, 2005, with variable duration.

The scope of the model includes optometrists from their first year of schooling to when they retire or permanently leave the profession (Figure 3). This scope is maintained regardless of reason for departure, be it disinterest, retirement from the local profession or attrition to the medical profession at either the undergraduate or professional levels. The scope of the model currently does not include optometrists that return to the profession after extended leave, or those who join the profession with their education already completed (for example, following immigration from another country). When agents enter the model in their first year of schooling, they are given a set of randomly generated attributes and preferences.

3.4 Design Concepts

A central advantage of ABM is that it allows for representing extremely fine-grained details at an individual level. This characteristic makes its combination with decision theory both highly natural (inasmuch as both ABM and DCE share a common point of reference in the individual) and powerful in its implications: agents are transformed from simple automatons with relatively simplistic dynamics to more complex and adaptive entities with a wider range of emergent behaviors and contextually adaptive responses. ABM also captures with relative grace the textured interactions between individuals within a population. This makes it a powerful tool for capturing supply and demand dynamics with respect to a resource that individuals may desire or compete over, such as places in an optometry program or jobs in the workforce. ABM's ability to capture aspects of inter-individual heterogeneity is central to our desire to understand workforce dynamics in a diverse population, and to represent varying preferences on the part of individuals and institutions. Finally, ABM's capacity to represent and to make choices contingent upon individual history can allow for representation of richer policy space, learning effects, and evolution of agent preferences.

Our realization of ABM makes use of what is known as *state charts*, a graphical depiction – formalized in UML (Fowler 2003) – of related states that an agent may occupy, and the transitions between them. Agents are in one and only one simple state within a specific state chart at any given time, known as the *active state*. Agents may have as many state charts as necessary; the states and transitions within a given state chart are primarily independent from states and transitions in other state charts. Viewed across state charts, a given state chart can be characterized as providing one dimension of an agent's heterogeneity. State charts may be "nested" within states; an example would be an agent being in the "in workforce" state, then further being in a sub-state that reflects their type of employment. Transitions may be triggered in response to events that occur at regularly scheduled intervals according to, for example, a fixed hazard rate or in response to messages that the agent receives.

Optometrist agents make decisions at regularly scheduled intervals, either coinciding with life events, such as choosing whether to drop out or not at the end of the school year, or at arbitrary time points, such as the decision to select a job. Selected decisions of optometrist agents within the model are characterized using RUT in such a way that the decision preferences for a given optometrist agent can be parameterized via information elicited from discrete choice experiments. Agent decisions are encapsulated within state-chart "branches" with each edge out of a decision node representing an outcome of a decision (Figure 3). Such branches represent a contingent transition, with the outcome being probabilistically determined based on agent preferences and characteristics of the choice set. An edge leading back to the state from which the transition originates corresponds to either a delay in making the decision or the decision outcome being "take no action".

To determine which outcome of a decision is selected, and to account for unobserved factors, the probability of selecting each outcome is computed using the logit model (Train 2003). The utility U_A of an outcome A is a linear combination of their personal preferences $\beta_1,\ldots,\beta_N$ (e.g., an agent's preference for a higher salary) and the associated factors $X_1,\ldots,X_n$ (e.g., the given salary of a job). Given *n* alternative outcomes, each of those with *C* associated factors, the probability of choosing outcome A, P(A), is then computed using

$$P(A) = \frac{\exp\left(\sum_{k=1}^{N} \beta_k^i X_k^i\right)}{\sum_{j=1}^{C}\sum_{k=1}^{N} \exp\left(\beta_k^j X_k^j\right)}$$

There is also a lambda term which is perfectly confounded with the betas and hence is typically normalized to one and omitted from the equation. This term is inversely related to the variance of the random utility ("error") term. Thus, a choice of "A" from the set [A, B, C] may have been made because the fixed (non-random) component of the utility of A is high, or the random components of the three items are small, are some combination of these; all of these explanations are observationally equivalent. In all cases the respondent is picking the item with the largest total utility: however, a large total utility can occur due to a large fixed or small random component.

For example, consider when an unemployed optometrist evaluates their career options. The optometrist has three options available to them: apply for some job supplied by an employer, start up a practice, or do nothing. Factors we have considered to govern this decision include: the expected monetary payoff of a particular job, whether or not the optometrist must relocate, and the amount of time commitment required. The utility for each job available, starting up a self-practice, and doing nothing are computed. A probability for each utility can be computed using the above formula (the probabilities for each job are conceptually grouped under the "apply for a job" transition for the purposes of agent state and calibrated using suitably sized random utility terms that approximately reproduce the choice probabilities from the DCE). Suppose the computed probabilities from the associated utilities for applying for a job, starting a self-practice, and doing nothing are 0.67, 0.04, and 0.29, respectively. That is, whenever an unemployed optometrist evaluates their career options, they are 67% likely to apply for a job, 4% likely to start up their own practice, and 29% likely to do nothing. If the agent probabilistically chooses to apply for a particular job, it then transitions to the appropriate employed state where it awaits to make additional decisions (in this case, whether to keep the job or begin the search for new career opportunities). Note that agents presently always acquire the job they applied for as the hiring process is underrepresented.

3.5 Initialization and Input

Optometrists' empirical demographics (Horton 1992; Horton 1996; Horton, Kiely, and Chakman 2006; Kiely et al. 2008; Kiely, Horton, and Chakman 2010), such as age and gender, are used to populate initial optometrists at the model's start and inform the attributes associated with an inflow of agents as time progresses. For example, Horton, Kiely, and Chakman (2006) noted that the trend in optometry is an increase in females entering the optometry profession, so the majority of newly created agents are female.

For this initial model at time of submission, agents:

- Do not learn at either an individual or collective level
- Are presently fully aware of all options currently available to them, such as the existence and characteristics of jobs in any given region
- Do not make any predictions (e.g., about future availability of options)

- Interact only indirectly: agents compete for jobs in the sense that once a job is filled by a given agent, it is no longer available for any other agent to take
- Do not belong to any reified collectives (e.g., a specific firm) or social networks
- While agents differ in demographics and preferences, they share the same underlying decision rule
- Exhibit static preferences: While preferences may change based on evolving situation (e.g. marital status), an agent’s preferences do not evolve over time
- Have just a single exemplar decision captured via RUT

4 CONCLUSION AND FUTURE WORK

Although the project described is at the proof of concept stage, we are confident that the combination of system dynamics, agent based modelling and random utility theory will better inform future policy planning by robustly modelling trends in the optometry profession and improving the quality of optometry graduates. By keeping agent preferences consistent with data obtained from discrete choice experiments, other aspects of the model could be varied to better capture the decisions and outcomes that the agents perform. Examples of variations include: the amount and type of information present to the agents such as job availability, the implications of additional optometry schools or schooling positions.

The model continues to evolve with the availability of more data and experience. Beyond the addition of support for characterizing additional decisions using RUT (which we anticipate being greatly enhanced by the time of the Winter Simulation Conference), some items being considered include the following:

- Optometrist agent dynamics will be better understood both from the professional and personal viewpoints. The design and refinement of our discrete choice experiments will inform additional types of decisions optometrists make.
- The results of the discrete choice experiments will inform what factors optometrists consider within a particular decision and the preferences associated with each factor.
- Refinement of existing stochastic processes such as those governing job attributes, including pay and employee requirements.
- Remedying the disparity between what the model considers as an optometrist “belonging to” a particular region (State), and what the official data suggests. For example, the model has no concept of optometrists being registered in more than one state.
- Explicitly representing employers and universities. Thus, the supply and demand dynamics of schooling seats and job creation are overly simplified.
- Incorporation of empirical preference data. The parameters governing agent’s decision making are currently ad hoc and not empirically grounded. Adequate experimentation, polling, and evaluation of real-life optometrist preferences are needed to appropriately inform the model and ground agent decision making in reality.
- The SD model governing population dynamics for each State could be improved. As it stands, population is always monotonically increasing in each state, and does not account for fluctuations in economic prosperity or quality of life.

Various implementation details could be improved in line with software engineering best practices. This would substantially ease further development of the model as features are changed and added.

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