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Modeling manpower requirement for a changing population health needs: The case of ophthalmic nurses and allied health ophthalmic professionals

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A B S T R A C T

Background: Prevalence of chronic eye conditions has been shown to increase with age. As the global population continues to age rapidly, the demand for eye care services is expected to increase significantly in the near future, requiring effective health workforce planning in order to provide for the needs of the population. The aim of this paper is to synthesize data from a variety of sources to develop a simulation model based on the systems modelling methodology of system dynamics that links population health needs to workforce requirements to generate evidence-based projections for ophthalmic nurses, and allied health ophthalmic professionals in Singapore.
Methods: A system dynamics simulation model was developed with active engagement of key stakeholders—such as ophthalmologists, senior nurses, healthcare planners and managers, and senior technicians—to verify the model structure and assumptions. The model project the future requirement of ophthalmic nurses, technicians and patient service assistants.
Results: The number of Singaporeans with eye diseases is projected to more than double by 2040. As a result, the demand for eye care services and eye care workforce is expected to increase significantly under all the plausible scenarios. The increase in eye disease burden is due mainly to population aging—given that the prevalence of eye disease increases with age.
Conclusion: This research provides a future demand outlook for ophthalmic nurses, technicians and patient service assistants in Singapore and has implications for recruitment and training of ophthalmic nurses and allied health professionals in Singapore.

Background

Prevalence of chronic eye conditions has been shown to increase with age [1–5]. As the global population continues to age rapidly, the demand for eye care services is expected to increase significantly in the near future, requiring effective health workforce planning in order to provide for the needs of the population. The risks of ineffective planning are huge: morbidity may increase, unmet healthcare needs may rise, waiting time to receive healthcare services may grow longer [6], quality of care may be compromised and huge sums of money wasted [7].

The aim of this paper is to synthesize data from a variety of sources to develop a simulation model based on the systems modelling methodology of system dynamics that links population health needs to workforce requirements to generate evidence-based projections for ophthalmic nurses, and allied health ophthalmic professionals in Singapore. This research is particularly vital and timely as Singapore and many other developing and developed countries sets out to confront increasingly complex healthcare needs presented by an aging and increasingly educated population with changing health needs and expectations. Singapore, in particular, has a high level of dependence on internationally recruited health professionals. In 2014, one in five medical practitioners employed in Singapore was of non-resident status

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Table 1
Attributes of methods considered.

Attributes of methods	Linear programming	Micro-simulation	Data-driven forecast	Econometrics	System dynamics
Stakeholder engagement					X
Causal mapping					X
Quantitative simulation modelling	X	X	X	X	X
Dynamic approach		X			X

(neither Singapore citizens nor permanent residents) [8]. This reliance on foreign health professionals is even stronger in the nursing sector. In the same year, one in four registered nurses and one in three enrolled nurses in Singapore were non-residents [9]. Recruitment of health workforce will become increasingly challenging as international competition for health professionals increase. Hence there is a compelling need to plan towards self-sufficiency.

To project future workforce requirements, we recognize the intrinsic uncertainties and complexities of the factors influencing the demand and supply of eye care workforce. Decisions made about workforce requirements need to work well across a range of future scenarios in order to be robust against uncertainty. To address this challenge, it is increasingly apparent that workforce planning must; (a) take a systems perspective and; (b) engage stakeholders to promote insight to and ownership of the projections. System dynamics is a method that applies systems perspective to problem analysis and offers a strong framework for analytic deliberation [10,11]. It is particularly useful for facilitating stakeholder engagement [12–16]. System dynamics has been applied primarily in business and public policy context [17–19] and is now increasingly being applied as a modelling paradigm for health workforce planning [20–26].

A brief literature review of methods

A brief literature review on common analytical methods applied to healthcare human resource planning—i.e. linear programming, microsimulation, data-driven forecasting, econometrics and system dynamics—was conducted. The attributes we considered in choosing the appropriate method for our research are: (a) stakeholder engagement—the method should lend itself to seamless engagement with diverse stakeholders to include different perspectives and promote insights and ownership of the projections; (b) causal mapping—the method should take a systems perspective and allow for translating outcomes from stakeholder's engagement into a causal map that captures concepts and their interrelationships from stakeholders perspective; (c) quantitative simulation modelling—the method chosen should have tools that allows for the development of quantitative simulation models for policy analysis and projections; and (d) dynamic approach—the quantitative model should be dynamic (not static) and able to address nonlinear relationships, time delays, information feedback and different scenarios and interventions simultaneously in a single framework. Table 1 shows the attributes of the methods considered in our review.

Linear programming

Linear programming is an optimization technique used to solve decision problems involving a single objective function and its constraints which are linear functions of decision variables [27]. The theoretical goal of linear programming is finding the set of positive decision variables that maximizes or minimizes the objective function. The main advantage of this method is the simplification of a real world problem into one that can be described with a linear relationship and the resultant simplicity allows for model variations to explore what-if analyses. The weakness of this method is that, linear programming can only solve decision problems with only one objective function. However, in practice, projecting requirements for healthcare human resources involves more than one outcome measure. Linear programming has been used to optimize nurse human resource planning in British Columbia [28], and cost-effectiveness of dental team skill-mix for England [29]. Linear programming methodology was found to be a good quantitative simulation method for optimizing decision problems, however, it lacks the tools for stakeholder engagement, causal mapping and the development of a dynamic model that account for time delays, information feedback and non-linearity over time.

Microsimulation

The increasing availability of healthcare data and faster computers has led to recent development of microsimulation models for healthcare human resource planning. What distinguishes microsimulation from other methods is the bottom-up approach. For healthcare human resource planning, demand for services are determined at the individual level and vary substantially by individuals in a representative sample of the population; while on the supply side, it is posited that career decisions are taken by individuals and household, hence the need to represent physicians', nurses and allied health professionals career decisions individually. A unique attribute of microsimulation is the ability to account for individual's demographics, health-related behaviors, socioeconomic factors, and other risk factors; thus increasing the accuracy of estimation of demand for care. The strength of microsimulation is the greater flexibility to model paradigm shifts in care delivery and policies that might affect specific patient groups, while the major drawbacks are its complexity, greater data requirements and increase processing time. Microsimulation methods has been applied to human resource for health planning in areas such as projecting future demand for and supply of health care workers in multiple professions and care settings [30], projecting the supply and demand of current and future US neurology workforce [31], projecting thoracic surgery workforce requirements in Canada [32], and to study the impact of population aging on specialized healthcare workforce demand [33]. Microsimulation method was found to be excellent method for developing quantitative simulation model for policy analysis and has the flexibility to capture important dynamics introduced by non-linearity, time delays and information feedback. However, the method lacks the tools to effectively and adequately engage stakeholders and map out outcomes from stakeholder engagement in a causal map to serve as an important input for the development of quantitative simulation models.

Data driven forecast

Data-driven forecasting involves the formulation of a series of equations to project human resource requirements. This method uses available data, such as patient visits, number of available physicians, work hours of physicians, and service uptake rate to predict the size of healthcare personnel required [34–36]. This method tends to be static and often do not account for expected future changes. However, the major advantage of this method is its ease of application. The data driven forecast method has been used to project nursing workforce [37], ophthalmologist supply and demand in Australia [38], physical therapy workforce in United States [39], cardiothoracic surgery workforce in Australia [40], project meeting human resources for health staffing goals in Zambia [41], and to predict physician assistant supply [36]. Data driven forecast method was found to be easy to use and has the capacity to develop quantitative model for projection; but static and lacks the tools for engaging stakeholders to map their mental models to inform quantitative analysis.

Econometrics

Econometrics is an amalgamation of statistics, mathematics and economics that takes into account the present and future constraints on resources to predict the healthcare human resources required. There are two types of econometric models: macro and micro models. In an econometric model, demand and supply interact and converge at an equilibrium point. Factors such as pricing, met and unmet needs that influence the market supply and demand are integrated into the method to evaluate the demand for healthcare personnel [42,43]. Econometric models are particularly useful for examining the relationships among stock, wages, demand, and budgets and are thus often used for evaluations on a state- or nation-wide scale [43–45]. Since this method mainly focuses on market factors that influence labor participation and healthcare utilization, other factors such as population health needs, impact of government policy, the influence of the changing health system and the impact of outcomes are not adequately accounted for [42]. Moreover, econometric models generally require extensive amounts of data which may often not be available. The application of econometrics to human resources for health estimates includes regional and sub-regional supply and demand forecast [43], and dental care prices, visits and workforce requirements [45]. Not unlike data driven forecast method, econometrics was found to be effective in developing static models to inform policy, however, lacks the tools for effective engagement with stakeholders which is vital for policymaking and consensus building.

System dynamics

System dynamics is a method for depicting and simulating dynamic behavior of health, economic and social mechanisms, based on information feedback, and the concept of stock and flow, delays, and nonlinearity. For brevity, the modeling process begins with defining a dynamic problem, proceeds through mapping and the modeling stages, to steps for building confidence in the model and its policy implications. In forecasting human resource requirements, there has been a recognition of the intrinsic uncertainties and complexities of the factors influencing the demand and supply of health professionals. An apparent advantage of system dynamics is its ability to (a) engage stakeholders in model development to improve understanding and ownership, (b) represent different parts of the health system in one single framework to facilitate comprehensive analysis of policy impacts, (c) address nonlinear relationships and different scenarios and interventions simultaneously in a single framework. Nevertheless, compared to microsimulation and other methods, system dynamics applies top-down approach in modeling aggregate decision change process, using aggregate stocks to represent groups. System dynamics models can be very complex as the number of variables and casual relations increases. The list of data input can increase rapidly making it difficult to populate. The application of system dynamics method to human resources for health planning has a broad scope including estimating the future requirement for and supply of ophthalmologists for an aging population in Singapore [25], pediatric workforce in Taiwan [46], forecasting the need for medical specialists in Spain [23], used to develop a framework for strategic workforce planning for healthcare at the national level [47], and forecasting shortage of physicians in Japan [22]. System dynamics was found to have all the four main attributes of stakeholder engagement, casual mapping, quantitative simulation modelling and dynamic approach to modelling. Thus this study adopted the system dynamics method for this research.

Methods

The Singapore Eye Care Model is a system dynamics model developed to project future demand for ophthalmic nurses, technicians and patient service assistants in Singapore under plausible scenarios. System dynamics [12–14] consists of an interconnecting set of differential and algebraic equations developed from a broad range of relevant empirical data [14]. The Singapore Eye Care model development process is as follows: first a consultation with stakeholders—ophthalmologists, senior nurses, healthcare planners and managers, senior technicians and patient service assistants—was organized to discuss the purpose of the model, identify outcomes of interest and discuss the scenarios to explore. After the consultation and further interactions with stakeholders, a conceptual model was developed and simulated to generate the current behavior over time pattern of key variables. Next, the conceptual model was presented to the core modeling team for the validation of model structure and assumptions. After validation, the model was populated with available data and when data is not available, estimates from experts were used. The Singapore Eye Care Model consists of four connected modules: the eye care demand module, nurse demand-supply module, technician demand-supply module and patient service assistant demand-supply module (see Figs. 1–4). The eye conditions included herein are myopia, epi-retinal membrane (ERM), retinal vein occlusion (RVO), age-related macular degeneration (AMD), diabetic retinopathy (DR), cataract, glaucoma and refractive error and other conditions. Other conditions include amblyopia, corneal conditions, posterior capsule opacification, pterygium, retinal scar, retinal dystrophy, optic disc, no obvious, aphakia, phthisis, trauma, squint, and others, an open category that includes all other eye diseases not classified into the previous 21 categories (see Appendix A for the definition of the eye diseases).

Data sources

Singapore Department of Statistics (SDS) provided the demographic data used as input to the population model [48]. On the eye conditions, ethnic (Chinese, Malays, and Indians), education (no formal, primary, secondary and tertiary) and age-specific prevalence estimates from the Singapore Epidemiology of Eye Disease (SEED) study [49–51] were used to project the number of people with eye conditions. The cross-sectional SEED study was conducted in southwestern Singapore in 2004 and 2011. Using an age-stratified random sampling strategy, 6752 Chinese, 5600 Malays, and 6350 Indians were selected from a registry of Singapore residents obtained from the Ministry of Home Affairs, of which 4605 Chinese, 4168 Malays, and 4497 Indians were deemed eligible to participate. A total of 3353 Chinese, 3280 Malays and 3400 Indians participated. The Ministry of Health, Singapore, provided administrative visit data for all the six public hospitals in Singapore, providing eye care services, from 2003 to 2013. In addition to the administrative data, Singapore National Eye Center—the biggest eye care hospital in Singapore, provided administrative case mix data, disaggregated by age and eye diseases as well as number and type of healthcare workers employed. The prevalence of eye diseases by ethnic, educational and age is provided in

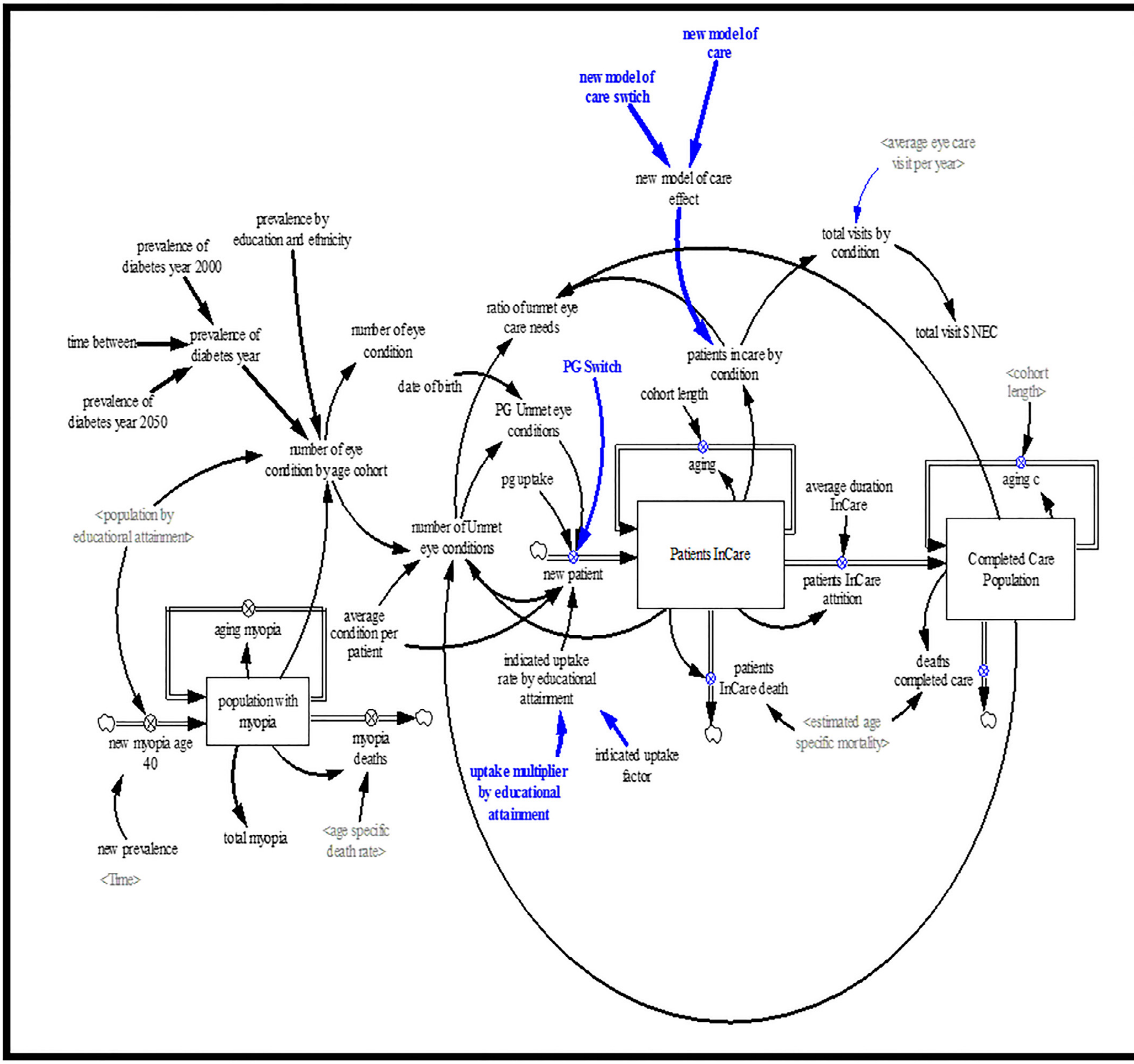

Fig. 1. Eye care demand module.

Appendix B1–B3. In addition, Table 2 below shows the list of input parameters to the simulation model.

Eye care demand module

The eye care demand module (see Fig. 1) has two main outputs: it projects the prevalence of eye diseases and demand for eye care services. To project prevalence of eye diseases, ethnic (Chinese, Malays, Indians and others), education (no formal, primary, secondary and tertiary) and age (40 and older disaggregated by single age cohort) specific prevalence estimate from the SEED study were used (see Appendix B1–B3). To project prevalence of eye diseases, ethnic, education and age-specific prevalence estimates were applied to a Singapore population model—which is described elsewhere [52–54]. Because the SEED study includes individuals 40 years and older, we were unable to project the prevalence of eye diseases among the population 40 years and younger.

Individuals with eye diseases were divided into three main categories—people with unmet eye conditions, patients in care and patient who have completed care. The stock of patients in care increase as patients with unmet eye care needs seek care for the first time (new patients) and decreases as care needs are met (patient attrition) and death. In the model, patients seeking care for the first time is determined by an uptake rate, which is assumed to be higher for individuals with high level of education. To account for mortality of patients in care, the population of patients in care is aged annually to ensure that age-specific mortality rates are applied to the appropriate age cohorts. The age-specific mortality rates were derived from life tables [48]. Patients in care attrition—which is applicable to only patients with non-chronic eye conditions such as cataracts, myopia and refractive error, whose care needs have been met—flow out to the completed care patient stock. It is estimated that the duration of treatment at the public specialist eye care centers (the focus of this paper) for cataracts,

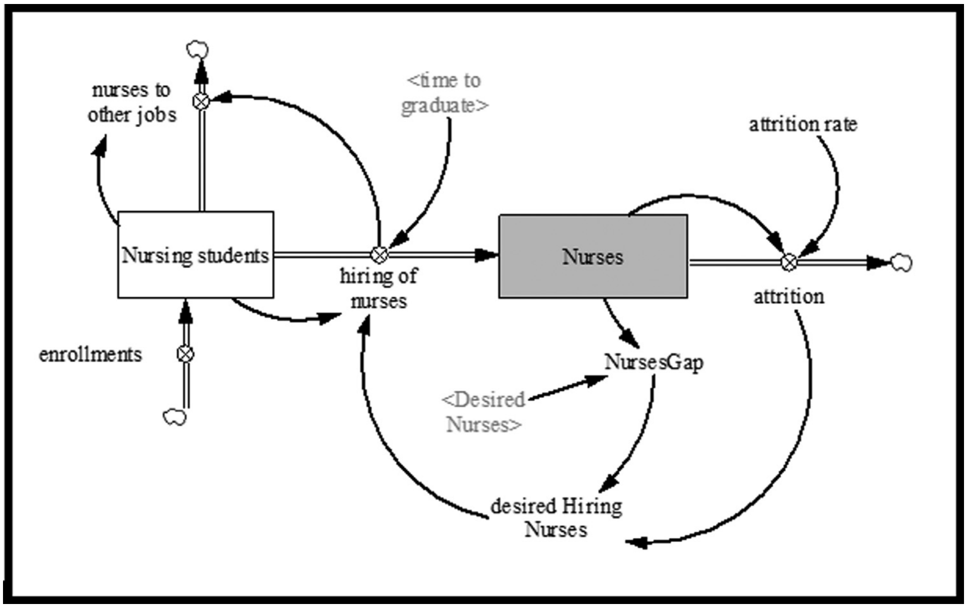

Fig. 2. Ophthalmic nurse demand-supply module.

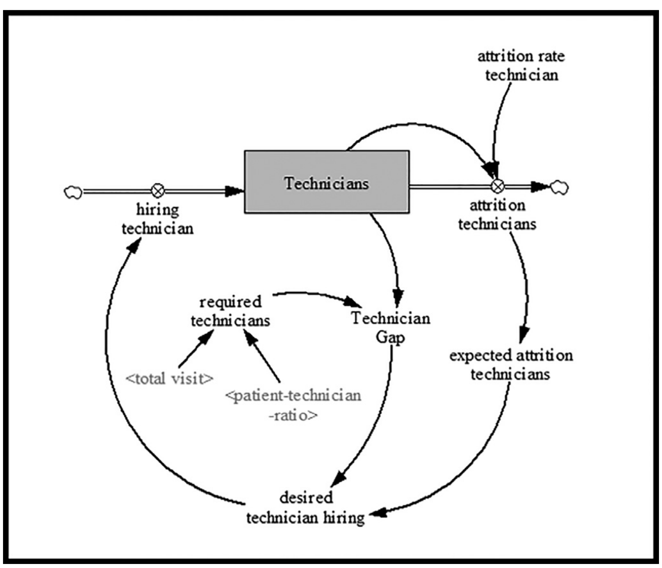

Fig. 3. Technician demand-supply module.

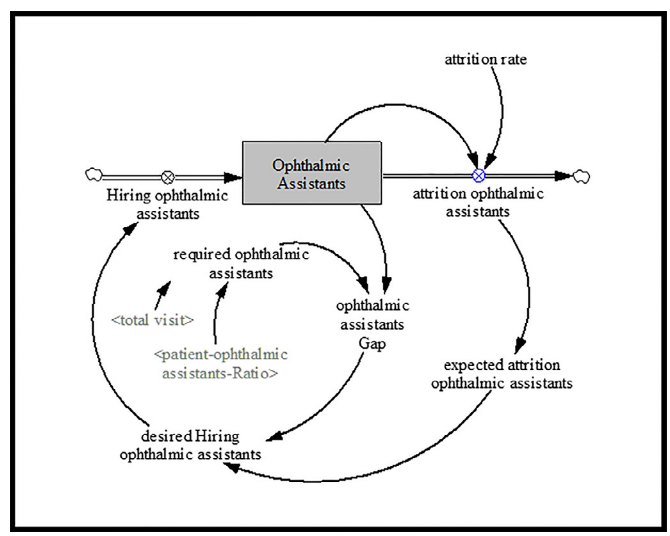

Fig. 4. Patient service assistant module.

myopia and refractive error are 3, 1 and 2 years, respectively. All other eye conditions are assumed to be chronic and require life-long care in the specialist eye centers. The completed care population increases as patient's complete care (patients in care attrition) and decreases via deaths. Like the patients in care stock, individuals in the completed care stock is aged annually and age-specific mortality rates derived from the life tables are applied to estimate deaths.

Demand for eye care services was estimated by multiplying average visits per patient in care by the number of patients in care.

Ophthalmic nurse demand-supply module

The ophthalmic nurse demand-supply module (see Fig. 2) is a continuous time compartment model that projects future demand for and supply of registered and enrolled ophthalmic nurses for the provision of eye care services in the public sector. The model uses utilization-based approach to project registered and enrolled ophthalmic nurse requirements. The future requirements for ophthalmic nurses is determined by total patient visits and estimated workload for registered and enrolled ophthalmic nurse. The ophthalmic nurse workload (patient-to-nurse ratio) is calculated using data from 2003 to 2012. On the supply side, the ophthalmic nurse demand-supply module uses stocks to track the current ophthalmic nurse population and the training pipeline of ophthalmic nurses. The current ophthalmic nurse population increases via hiring of new ophthalmic nurses and decreases by attrition. Hiring of new ophthalmic nurses is formulated in the model as the minimum between graduate nurse population and desired nurse hiring. Desired hiring is the summation of the ophthalmic nurse gap and expected attrition. Ophthalmic nurse gap is the difference between ophthalmic nurse requirements and current ophthalmic nurses: where a positive number suggests undersupply and a negative implies oversupply. Graduated nurses not hired to provide eye care services in the public sector are assumed to seek employment in other parts of the health care sector. In the model, we assume a 3% attrition rate and dropout rate of zero. In addition, average time to

Table 2
Model inputs.

Variable name	Value	Unit	Source
Demand Module			
Uptake factor [no education]	0.045	Dimensionless/year	Model calibration
Uptake factor [primary]	0.07	Dimensionless/year	Model calibration
Uptake factor [secondary]	0.076	Dimensionless/year	Model calibration
Uptake factor [tertiary]	0.15	Dimensionless/year	Model calibration
Average Duration			
Cataracts	3	Year	Expert Opinion
Myopia	1	Year	Expert Opinion
Refractive Error	2	Year	Expert Opinion
Age-specific mortality rate	Time series [2002–2013)	Dimensionless/year	Department of statistics
Distribution of Patients			
Cataracts	0.31	Dimensionless	Case mix study at SNEC
DR	0.09	Dimensionless	Case mix study at SNEC
Glaucoma	0.17	Dimensionless	Case mix study at SNEC
AMD	0.03	Dimensionless	Case mix study at SNEC
Myopia	0.02	Dimensionless	Case mix study at SNEC
Refractive Error	0.02	Dimensionless	Case mix study at SNEC
ERM	0.01	Dimensionless	Case mix study at SNEC
RVO	0.01	Dimensionless	Case mix study at SNEC
Others	0.34	Dimensionless	Case mix study at SNEC
Population of completed care			
Cataracts	0.1	Dimensionless	Model assumption
Myopia	0.1	Dimensionless	Model assumption
Refractive Error	0.1	Dimensionless	Model assumption
Average eye care visits	2.4	Visit/patient/year	Expert Opinion
Nurse Module			
Attrition rate			
Registered nurse	0.02	Dimensionless/year	Model calibration
Enrolled nurse	0.05	Dimensionless/year	Model calibration
Average time to complete school			
Registered nurse	3	Year	Expert Opinion
Enrolled nurse	2	Year	Expert Opinion
Dropout rate	0	Dimensionless/year	Expert Opinion
Visit-nurse ratio	Time series [2000–2013]	Visit/worker/year	MOH
Enrolment per year	Time series [2000–2013]	Student/year	MOH
Technician Module			
Attrition rate	0.02	Dimensionless/year	Model calibration
Visit-technician ratio	Time series [2000–2013]	Visit/worker/year	MOH
Ophthalmic Assistant Module			
Attrition rate	0.05	Dimensionless/year	Model calibration
Visit-technician ratio	Time series [2000–2013]	Visit/worker/year	MOH

complete nursing school is assumed to be 3 years for registered nurses and 2 years for enrolled nurses.

Technician demand-supply module

The technician module (see Fig. 3) projects future demand for technicians and correspondingly tracks the number of technicians employed to provide eye care services in the public sector, with a continuous time compartment model. The future technician requirements (technician demand) is determined herein using the utilization-based approach. The utilization based approach projects future eye care patient visits under plausible futures and estimate the number of technicians required to provide eye care services. Desired technician hiring determines hiring of technicians. Desired technician hiring is defined as the sum of technician gap and expected attrition, whereas, technician gap is the difference between technician requirements (technician demand) and employed technicians. Attrition rate of technicians is estimated by calibration.

Patient service assistants demand-supply module

The patient service assistant demand-supply module (see Fig. 4) projects future patient service assistant requirements (patient service assistant demand) and also tracks the number of patient service assistant employed to support the provision of eye care services in the public sector. The stock of patient service assistant employed to support the provision of eye care services in the public sector increases via hiring and decreases via attrition. Attrition rate is estimated by calibration. Like the other previous modules, hiring is determined by desired patient service assistant hiring (patient service assistant demand). Desired patient service assistant hiring is the sum of expected attrition and patient service assistant gap; whereas patient service assistant gap is the difference between patient service assistant requirements (patient service assistant demand) and employed patient service assistant in the public sector. Attrition rate of 3% is assumed for patient service assistant.

Scenarios

Business-as-usual

This scenario assumes that current model parameters remain unchanged over the simulation time. The scenario is unlikely as some of these parameters are expected to change over time, however, it was included to serve as a reference point for comparison with other scenarios.

Current policy

Under this scenario, uptake rate of eye care services is assumed to change, as screening for eye care conditions at the community

Table 3
Prevalence of eye condition for resident Singaporeans 40 years and older.

Eye Condition	Base Year	Projected						% change from 2015–2040
	2010	2015	2020	2025	2030	2035	2040	
Cataract	590,019	739,404	900,297	1,054,809	1,186,115	1,283,599	1,345,318	82
DR	92,059	116,541	144,124	172,797	200,397	225,809	248,638	113
Glaucoma	59,273	75,389	93,802	112,694	129,894	143,374	152,125	102
AMD	106,573	125,795	145,704	164,667	180,398	190,794	194,908	55
Myopia	957,072	1,148,139	1,317,953	1,483,793	1,654,857	1,818,665	1,954,921	70
Refractive Error	323,625	359,498	385,507	403,512	416,948	428,363	438,641	22
ERM	217,144	276,141	340,977	405,037	461,620	508,206	544,869	97
RVO	12,600	14,366	15,918	17,361	18,774	20,055	21,051	47
Other Conditions	73,545	90,536	109,953	131,444	153,975	174,636	190,472	110

level via mobile eye clinic increase, rise in awareness and availability of eye clinics in the community as well as increased subsidies for eye care services. Uptake rate is assumed to change from 4.5% to 13% by 2040 for individuals with no education, while the change for individuals with primary, secondary and tertiary educated are 20%, 21% and 46%, respectively.

New model of care

Under this scenario, 20% of patients with DR, and glaucoma, as well as 90% of those with myopia and refractive error, will be decanted from specialist outpatient clinics to primary eye clinics to be cared for by non-specialist.

Moderated workload

This scenario assumes 15% reduction in current clinical workload due to effort to pursue non-clinical goals to improve work-life balance and patient's care.

Model validation and sensitivity analysis

The validation of the Singapore Eye Care Model focused on behavior test—which is the ability of the model structure to replicate past data; and structural test—which focus on the validity of the model structure and equations [13]. The behavior test shows that simulated behavior of key variables compared favorably to available data (see Appendix C) for registered and enrolled nurses, as well as technicians and patient service assistants. The validity of the model was further reinforced by conducting a mean absolute percentage error (MAPE) and Theil statistic tests [55]. The MAPE which is a measure of prediction accuracy for registered nurses, enrolled nurses, technicians and patient services assistants were 9.57%, 12.48%, 13.68% and 13.15%, respectively. The result indicate that the simulated model compares well with available data. For the Theil statistics, the error due to bias (U^M) for registered nurses, enrolled nurses, technicians and patient service assistant were 0.3%, 6.2%, 6% and 15%; while that for unequal variance (U^S) were 70%, 77.8%, 76.8% and 53.9%; and the error for covariance component (U^C) were 29.7%, 16%, 17.3% and 31.1%, respectively. Thus, all the outcome variables have majority of the error within the unequal variance (U^S) as compared to bias (U^M) and covariance component (U^C). This suggest that simulated outcomes track underlying trend well and that the majority of the errors are unsystematic with respect to the purpose of the model. For structural test, the model was presented on several occasions to stakeholders which included ophthalmologist, senior ophthalmic nurses, healthcare planners and managers, senior technician and personal service assistants, to verify the structure and assumptions of the model regarding model conceptualization and causal relationships. Thus, the model is firmly grounded in current literature and evidence on eye care services.

On sensitivity analysis, Markov Chain Monte Carlo (MCMC) approach [56] was used on all scenario to assess how a change in uptake factor—the most important model parameter—affect the outcomes of interest. The model was run 24000 times and the minimum and a maximum value at 95% confidence interval as well as the average of the simulation was used to show the credible interval of the estimates.

Results

Prevalence

The projected prevalence of various eye conditions in resident Singaporeans aged 40 years and older up to the year 2040 are shown in Table 3. All the eye conditions considered herein are projected to increase. The eye diseases with the greatest percentage change over the years 2015 to 2040 are DR, other conditions, glaucoma and ERM, with increases of 113%, 110%, 102% and 97% respectively. The remaining conditions also exhibited growths ranging from 22% to 82% over the same time period.

In terms of absolute numbers, the three most prevalent conditions are myopia, cataract, and refractive error, with 1,148,139, 739,404 and 359,498 cases in 2015 respectively. Myopia remains the most prevalent condition over the years, with a projected 1,954,924 cases in 2040. This is followed by 1,345,318 cataracts and 544,869 ERM cases by the year 2040 respectively. The remaining conditions are projected to have less than 440,000 cases and are listed in decreasing order of prevalence: refractive error, DR, AMD, other conditions, glaucoma and RVO.

Lastly, disaggregated analysis shows that the projected increase in eye care needs is due mainly to population aging and not population growth. Population growth only account for between 1%–21% of the change in eye care needs from year 2010 to 2040.

Patient visits

Patient visits in Singapore are expected to increase over the years 2015 to 2040 under all four scenarios. The percentage increases in each scenario, in ascending order, are as follows: business-as-usual (114%), moderated workload and new model of care (both 132%) and current policy (155%). If the status quo is kept, patient visits are projected to increase from 837,854 in 2015 to 1,792,228 in 2040 (sensitivity analysis: 1,799,810–1,834,767). With the current policy, patient visits are predicted to increase to 2,220,233 (2,218,553–2,243,723) in 2040, up from 869,278 in 2015. Likewise, there is an anticipated growth in patient visits for both the new model of care and moderated workload scenarios from 869,278 in 2015 to 2,015,292 (2,015,166–2,038,865) in 2040.

Table 4
Sensitivity analysis results of required registered nurses, required enrolled nurses, required technicians and required ophthalmic assistants in Singapore.

Outcome	Base Year	Projected						% change from 2015–2040
	2010	2015	2020	2025	2030	2035	2040	
Required registered nurses for Singapore								
Business-as-usual	174 [140–236]	318 [263–409]	420 [369–512]	498 [436–586]	570 [496–669]	632 [543–743]	681 [579–799]	114
Current policy	174 [140–236]	330 [274–424]	493 [442–584]	613 [554–689]	707 [639–783]	785 [708–862]	843 [761–922]	155
New Model of Care	174 [140–236]	330 [274–424]	477 [427–566]	583 [524–657]	663 [599–736]	724 [652–799]	766 [689–840]	132
Moderated workload	174 [140–236]	332 [276–426]	494 [442–586]	623 [560–701]	730 [660–811]	824 [742–909]	901 [811–989]	171
Required enrolled nurses for Singapore								
Business-as-usual	107 [86–144]	195 [161–251]	257 [226–314]	305 [267–359]	349 [304–410]	387 [333–455]	417 [355–490]	114
Current policy	107 [86–144]	202 [168–260]	302 [271–358]	376 [339–422]	433 [392–480]	481 [434–529]	517 [467–565]	155
New Model of Care	107 [86–144]	202 [168–260]	292 [261–347]	357 [321–402]	406 [367–451]	444 [400–490]	469 [422–515]	132
Moderated workload	107 [86–144]	204 [169–261]	303 [271–359]	382 [343–430]	448 [404–497]	505 [455–557]	552 [497–606]	171
Required technicians for Singapore								
Business-as-usual	36 [29–49]	64 [53–82]	85 [74–103]	100 [88–118]	115 [100–135]	127 [109–150]	137 [117–161]	114
Current policy	36 [29–49]	67 [55–85]	99 [89–118]	124 [112–139]	142 [129–158]	158 [143–174]	170 [153–186]	155
New Model of Care	36 [29–49]	67 [55–85]	96 [86–114]	117 [106–132]	134 [121–148]	146 [131–161]	154 [139–169]	132
Moderated workload	36 [29–49]	67 [56–86]	99 [89–118]	125 [113–141]	147 [133–163]	166 [149–183]	181 [163–199]	171
Required ophthalmic assistants for Singapore								
Business-as-usual	77 [62–104]	121 [100–155]	159 [140–194]	189 [165–222]	216 [188–254]	240 [206–282]	258 [219–303]	114
Current policy	77 [62–104]	125 [104–161]	187 [168–221]	232 [210–261]	268 [242–297]	297 [268–327]	320 [288–349]	155
New Model of Care	77 [62–104]	125 [104–161]	181 [162–214]	221 [199–249]	251 [227–279]	274 [247–303]	290 [261–318]	132
Moderated workload	77 [62–104]	126 [104–162]	187 [167–222]	236 [212–266]	277 [250–307]	312 [281–344]	341 [307–375]	171

Workforce requirements

As indicated in Table 4, 318 and 681 (579–799) registered ophthalmic nurses are needed in the years 2015 and 2040 respectively when considering the business-as-usual scenario. Both the current policy and new model of care scenarios require 330 registered ophthalmic nurses in 2015. The former projects a demand for 843 (761–922) registered ophthalmic nurses in 2040 while the latter, 766 (689–840) registered ophthalmic nurses in the same year. If the workload is moderated, 332 registered ophthalmic nurses are required in 2015 and 901 (811–989) in 2040.

The business-as-usual scenario projects a need for 195 and 417 (355–490) enrolled ophthalmic nurses in 2015 and 2040 respectively. Similarly, 202 enrolled ophthalmic nurses in 2015 for both the current policy and new model of care scenarios are expected to increase to 517 (467–565) and 469 (422–515) in 2040 for each corresponding situation. In the case of a moderated workload, the number of enrolled ophthalmic nurses required in 2015 is 204 and rises to 552 (497–606) in 2040.

In the business-as-usual scenario, 64 technicians are needed in 2015 and increases to 137 (117–161) in 2040. For the other three scenarios, 67 technicians are deemed necessary to meet the demands of the public sector eye care needs in the year 2015. This number is expected to increase for all three scenarios in 2040, with 170 (153–186) technicians required under the current policy, 154 (139–169) technicians for a new model of care and 181 (163–199) technicians when workload is moderated.

The requirement of 121 patient service assistants in 2015 is projected to increase to 258 (219–303) in the year 2040 if business continues as usual. Both the current policy and new model of care scenarios require 125 patient service assistants in 2015. In 2040, the former projects a need for 320 (288–349) patient service assistants while the latter projects a demand for 290 (261–318) patient service assistants. When considering the moderated workload scenario, 126 and 341 (307–375) patient service assistants are required in 2015 and 2040 respectively.

Discussion

The number of Singaporeans with eye diseases is projected to more than double by 2040. As a result, the demand for eye care services and eye care workforce is expected to increase significantly under all the plausible scenarios experimented in this study. The increase in eye disease burden is due mainly to population aging—given that the prevalence of eye disease increases with age. The population of Singapore is expected to increase from 5.5 million in 2015 to 6.9 million by 2040, of which the population 60 years and older is projected to more than double within the same time. Furthermore, government policies such as the introduction of mobile eye clinics for screening among the elderly in the community, and increasing subsidies to improve healthcare affordability are projected to drive demand for eye care services. In addition, the expected increase in educational attainment among the elderly will lead to higher visual acuity expectations; coupled with technological innovation, these trends will drive the demand for eye care services, hence the need for proactive planning to meet future demand.

The finding that eye care service needs and demand are expected to increase as population ages has implications for policymakers in Singapore and countries with rapidly aging population such as Japan, South Korea, China, USA, and United Kingdom. First, the finding suggests that policymakers should be proactive in planning for appropriate services to meet the needs of the population. Inability to meet eye care needs of the population—especially the elderly—will impact quality of life and the ability of the elderly to have independent life (i.e. to perform activities of daily living (ADL) and instrumental activities of daily living (IADL)), consequently increasing family care burden and healthcare cost. In addition, if due to planning delays adequate care services are not provided morbidity may increase, unmet healthcare needs may rise, waiting time to receive healthcare services may grow longer, and quality of care may be compromised. Second, the findings have implications for training and retaining adequate human resources for health to provide healthcare services in general and eye care needs in particular for the population. It is important for policymakers to periodically estimate the future healthcare needs of the population and proactively develop strategies to train and recruit human resources to meet care needs, due to the significant delays in training health professionals. In Singapore, this has impact on the recruitment of nurses and allied health professionals working in the eye care sector, where there is a high level of dependence on internationally recruited health professionals. Recruitment of health workforce will become increasingly challenging as international competition for health professionals increase. Hence there is a compelling need to plan towards self-sufficiency. Also, the significant expected increase in the demand for nurses and allied health professionals for eye care services has cost and infrastructural implications. As demand for eye care services increase, government expenditure on healthcare is likely to increase, hence the need to have clear understanding of future workforce requirements and thus explore alternative cost-effective ways of providing these services. Third, given the general increase in educational attainment of the population both in developed and developing world, and the increasing uptake of technology, policymakers should explore the possibilities of shifting some of the care provided currently at the hospital directly into patients hands to reduce or moderate the expected increase in eye care services. Such intervention may decrease the demand for health professionals and raise the proportion of patients activated in their own care—which is associated with better health outcomes. Lastly, the finding has implications for competition for health professionals. Understanding the likely impact of this competition on the availability of health professionals will be essential for policymakers—especially for developing counties that export health professionals and developed countries where foreign health professionals constitute significant fraction of their workforce. Effective proactive planning will facilitate learning and generation of deeper understanding of future scenarios which may lead to strategies for addressing plausible futures to ensure the availability of adequate and motivated health professions to meet the care needs of the population.

The strength of our study includes the use of large representative data on the epidemiology of eye diseases, and detailed administrative data on eye care services utilization, and current available workforce. Nevertheless, the study is not without limitations. The use of prevalence instead of incidence to estimate future disease burden may over or under estimate future eye disease burden. Furthermore, the projection focused only on individuals 40 years and older, but any pathological condition with higher or lower prevalence among the population 40 years or younger may affect the projected numbers.

The methodology and approach used in this research to understand the likely future requirements for eye care services needs and its impact on health human resources—in particular for ophthalmic nurses and allied health professionals—is conceptually similar to the Robust Workforce Planning Framework which was recently described in a publication as cited [47]. The Robust Workforce Planning Framework consists of four key stages: (a) horizon scanning which defines the future issues affecting the workforce of interest; (b) scenario generation which identifies how the future issues will occur in a structured way; (c) workforce modelling to generates dynamic projections across different scenarios; and (d) policy analysis to define robust policies for the workforce to face the scenarios. Our approach—in developing the Singapore Eye Care Model—aligned with the four stages described in the Robust Workforce Planning Framework. Through active stakeholder engagement, we were able to identify the major issues that the stakeholders considered are likely to affect demand for eye care services and consequently eye care workforce. This factors informed the scenario generation as well as the conceptualization of the model. The scenario generation process also considered current policies under consideration in Singapore to inform decision making. The workforce modelling process—which is described in the methodology section—is based on current knowledge and broad range of relevant empirical data with significant input from stakeholders, drawing on their complex personal experiences, beliefs, and perceptions through moderated interactions. The results from the modelling exercise has been shared with policymakers to inform decision making and future planning. This clearly shows that our methodology is consistent with current approaches to strategic workforce planning in the healthcare sector. What our approach contribute to the literature on workforce planning is the emphasis on the active engagement of stakeholders in the whole modelling process to develop insights that change mental models, which in turn leads to changes in decisions and aid the process of implementation modelling insights.

Conclusion

This research provides a future demand outlook for ophthalmic nurses, technicians and patient service assistants in Singapore. The insight that prevalence of eye diseases will increase due to population aging; and consequently, demand for eye care services is expected to rise due in part to increasing assess to care, higher visual acuity expectations of the population (especially the elderly) becuase of high educational attainment has policy implications for health resource planning and workforce policy in Singapore and developed and developing countries experiencing aging population. Here we systematically show why demand for eye care services in Singapore is expected to increase, and its implication for health workforce requirement and why system dynamics methodology allows for exploring what-if scenarios to inform policy. We hope that the insights gained will inform human resources planners and policy makers in Singapore and countries with aging population to proactively and periodically assess the health needs of their population and its impact on demand for healthcare professionals, while identifying sustainable strategies to meet future eye care needs of the population. The modelling approach used herein offers policymakers the opportunity to test policies in-silico to learn about the likely impacts and unintended consequences before deciding on implementing such policies to avoid costly mistakes.

Authors contribution

All authors contributed sufficiently to quality as co-author. All authors read and approved the final manuscript.

Author statements

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Competing interests

None declared.

Ethical approaval

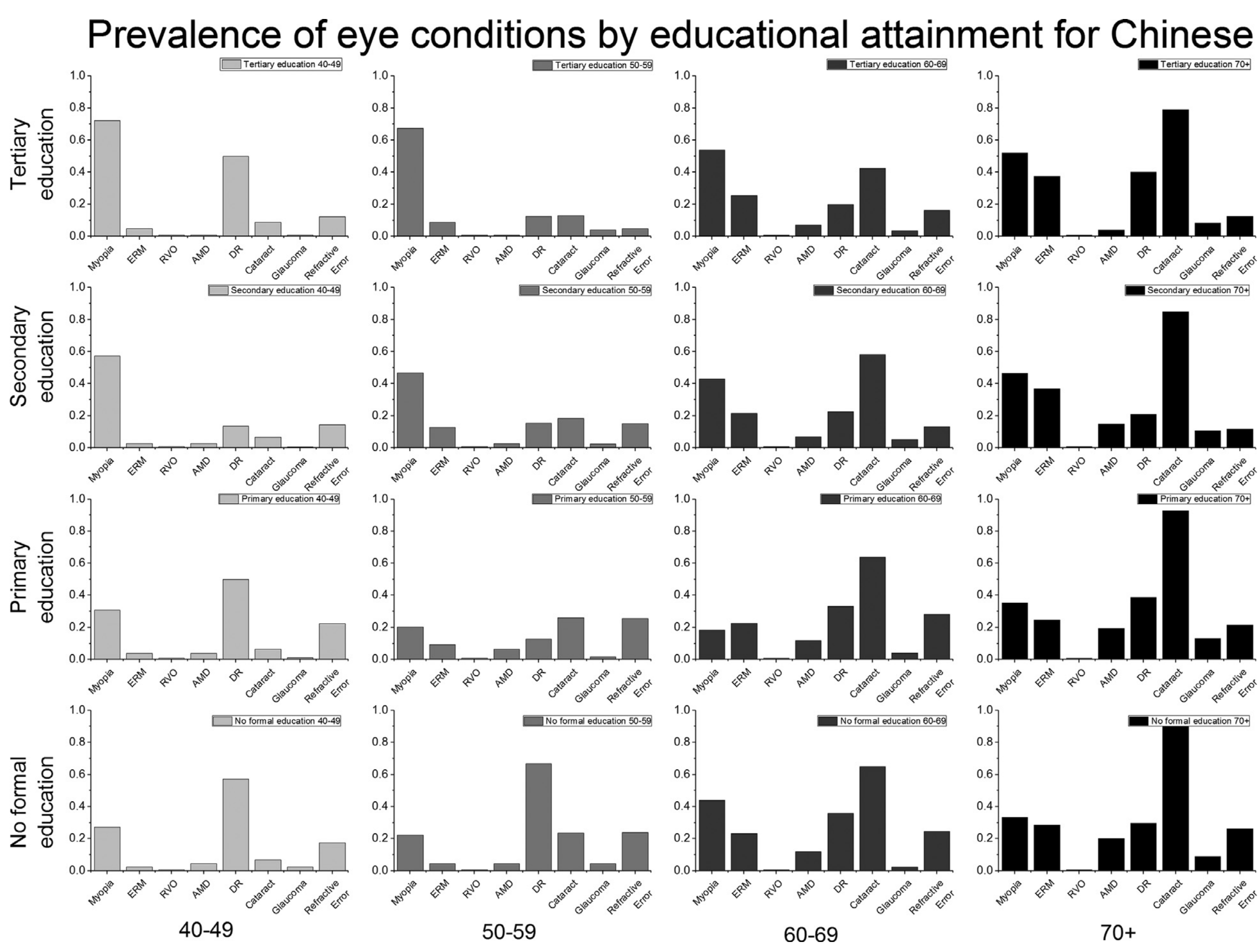
This research did not require ethical approval as publically available data was used. IRB was deemed unnecessary according to the national guidelines.

Appendix A

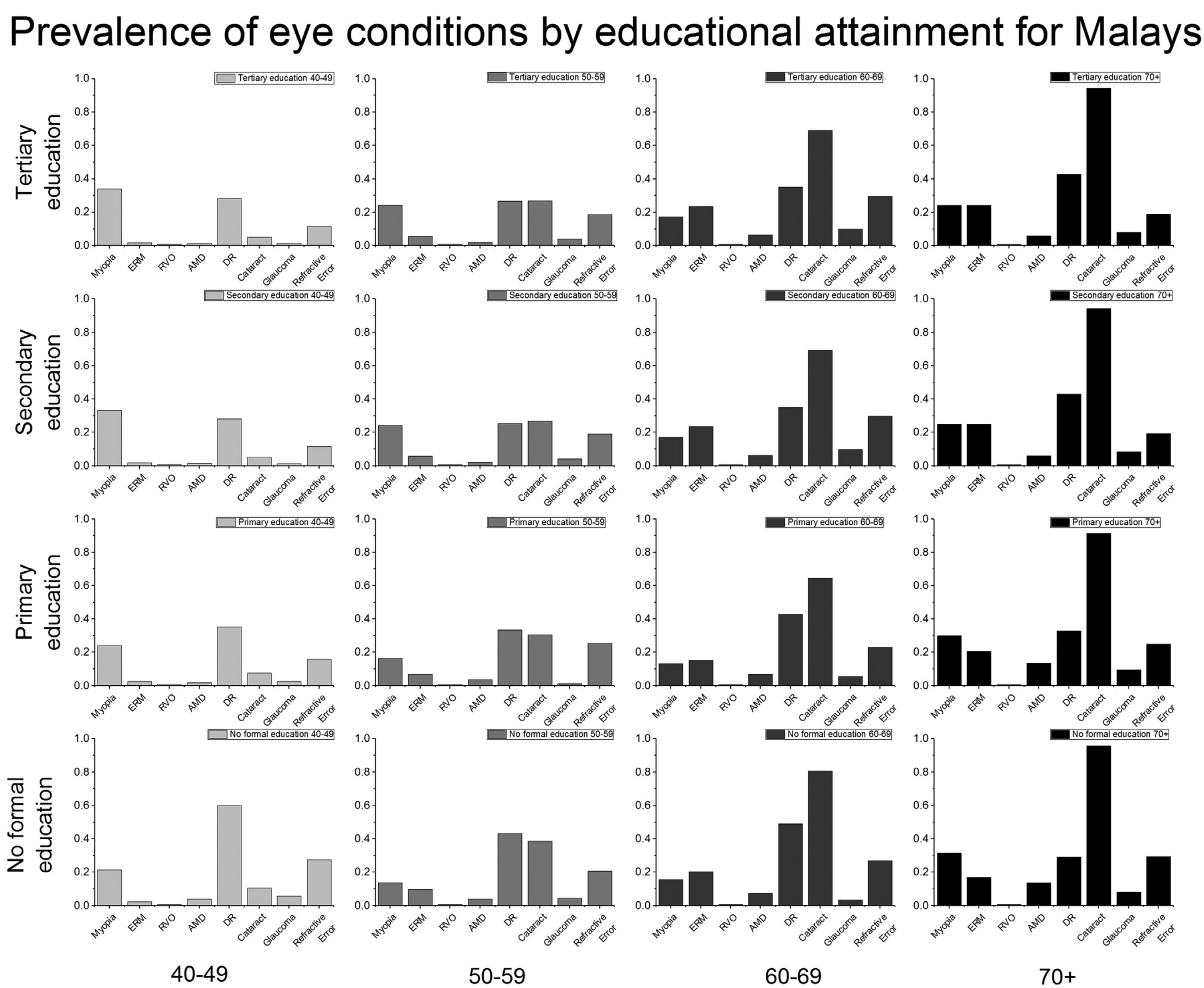
Table A1
Definition of eye diseases.

Condition	Definition
Myopia	Myopia is defined as spherical equivalent (SE) of less than −0.5 Diopter
Refractive Error	Refractive Error is defined as the difference between Presenting visual acuity and Best Corrected visual acuity is no less than 0.2 LogMar
ERM	ERM is defined with either Surface wrinkling retinopathy (preretinal fibrosis), with folds, tension lines or a patch, or Cellophane reflex only or Macular pucker
RVO	RVO includes Branch retinal vein occlusion, or Central retinal vein occlusion
AMD	Early AMD was defined as presence of either any soft drusen (distinct or indistinct) plus pigmentary abnormalities, reticular drusen, or large soft drusen >125 μm in diameter with drusen area >500μm-diameter. Late AMD was defined as the presence of neovascular AMD or geographic atrophy (GA). Neovascular AMD included serous or hemorrhagic detachment of the RPE or sensory retina, and the presence of subretinal or sub-RPE hemorrhages or subretinal fibrous scar tissue. GA was characterized by sharply edged, roughly round or oval areas of RPE hypopigmentation, with clearly visible choroidal vessels. The minimum diameter of GA was 175um, or larger. All CFP were graded initially in a masked manner and discrepancies were adjudicated by a senior retinal specialist
DR	DR was considered present if characteristic lesions as defined by the Early Treatment Diabetic Retinopathy Study (ETDRS) (i.e. microaneurysms, haemorrhages, cotton wool spots, intraretinal microvascular abnormalities, hard exudates, venous beading, new vessels) were observed. DR severity was graded based on the modified Airlie House classification system, using the Blue Mountains Eye Study protocol. Individuals' DR status was defined based on the severity scores of the worse eye. Clinically significant macular edema (CSME) was considered present when the macular edema involved was within 500 μm of the foveal center or if focal photocoagulation scars were present in the macular area. VTDR was defined as the presence of severe non-proliferative DR, proliferative DR or CSME
Cataract	Cataract was defined using the Wisconsin Cataract Grading System. In our previous study, using the Wisconsin cataract grading, we defined cortical and PSC cataract as >=5% and >0% of total lens area, respectively. In the current study, nuclear cataract was defined as grade 4 or more, cortical cataract was defined as >=25% of total lens area, and PSC cataract was defined as >= 5% of total lens area. Any cataract was defined as nuclear, cortical, or PSC cataract in at least 1 eye.
Glaucoma	Glaucoma was defined according to the International Society of Geographical and Epidemiological Ophthalmology (ISGEO) criteria based on 3 categories.In brief, category 1 cases were defined as optic disc abnormality (VCDR or VCDR asymmetry ≥97.5 percentile) with a corresponding glaucomatous visual field defect. Category 2 cases were defined as having a severely damaged optic disc (VCDR or VCDR asymmetry ≥99.5th percentile) in the absence of reliable visual field test results. Category 3 cases were defined for subjects who were blind (corrected visual acuity of <3/60), were without visual field or optic disc data, and had previous glaucoma surgery or IOP >99.5 percentile.

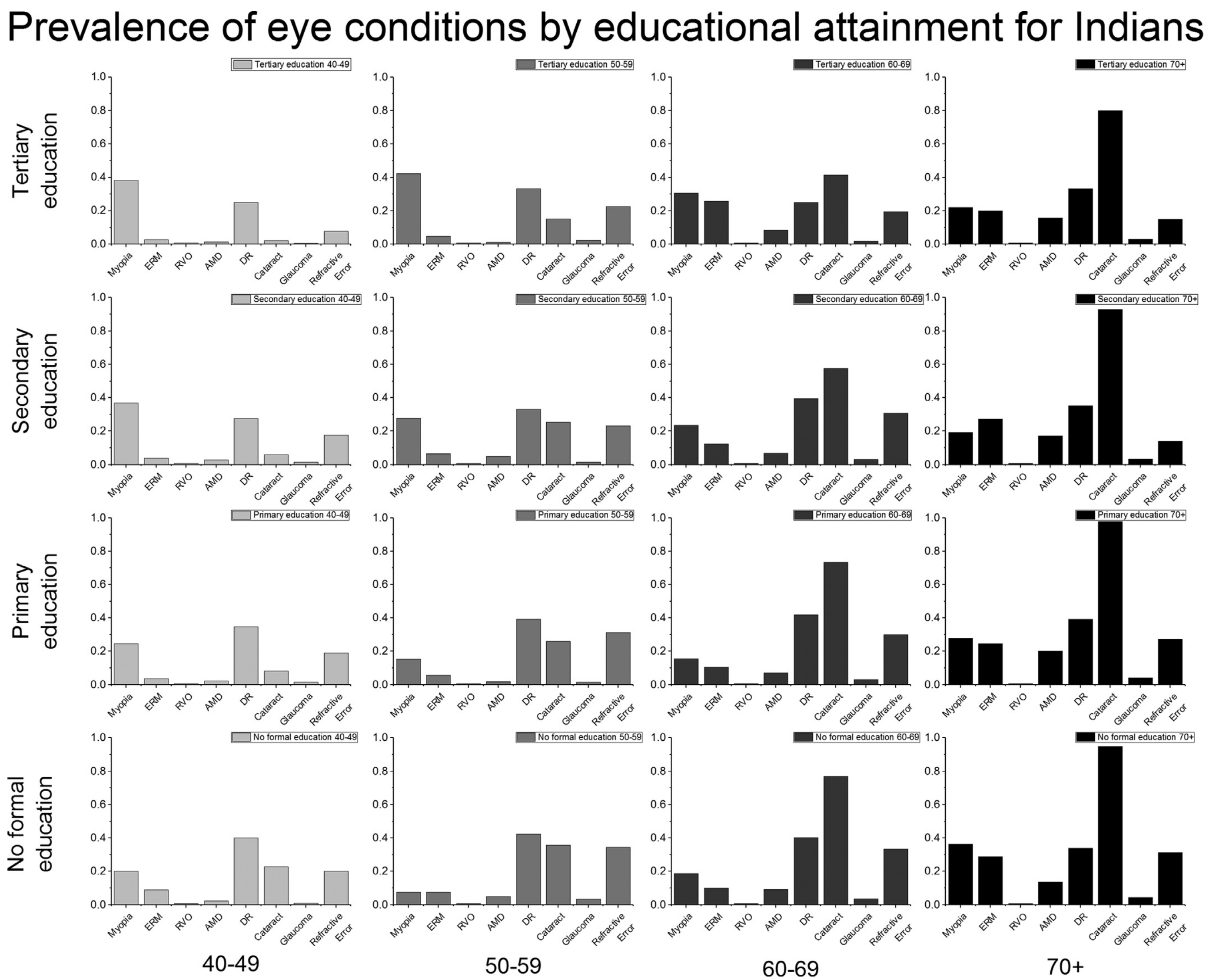
Appendix B1



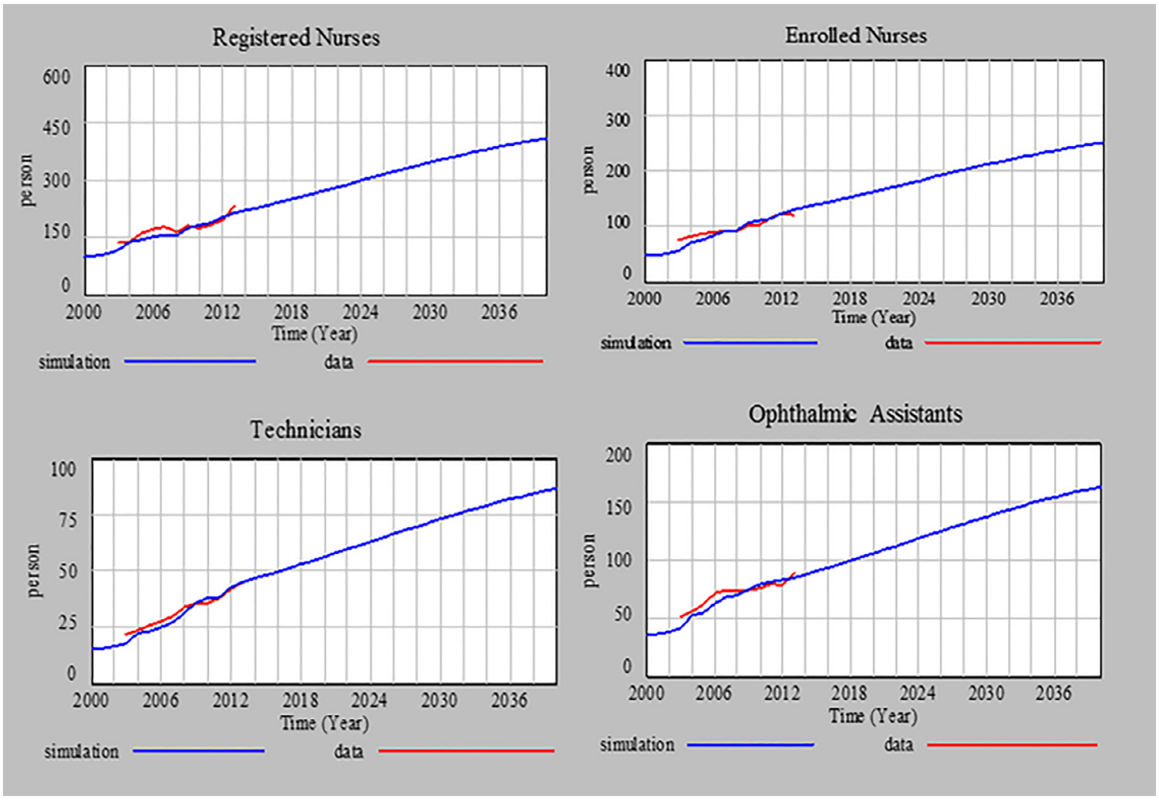
Appendix B2


Prevalence of eye conditions by educational attainment for Malays
Tertiary education
Secondary education
Primary education
No formal education
Tertiary education 40-49
Tertiary education 50-59
Tertiary education 60-69
Tertiary education 70+
Secondary education 40-49
Secondary education 50-59
Secondary education 60-69
Secondary education 70+
Primary education 40-49
Primary education 50-59
Primary education 60-69
Primary education 70+
No formal education 40-49
No formal education 50-59
No formal education 60-69
No formal education 70+
Myopia
ERM
RVO
AMD
DR
Cataract
Glaucoma
Refractive Error
40-49
50-59
60-69
70+

Appendix B3


Prevalence of eye conditions by educational attainment for Indians
Tertiary education
Secondary education
Primary education
No formal education
40-49
50-59
60-69
70+
Tertiary education 40-49
Tertiary education 50-59
Tertiary education 60-69
Tertiary education 70+
Secondary education 40-49
Secondary education 50-59
Secondary education 60-69
Secondary education 70+
Primary education 40-49
Primary education 50-59
Primary education 60-69
Primary education 70+
No formal education 40-49
No formal education 50-59
No formal education 60-69
No formal education 70+
Myopia
ERM
RVO
AMD
DR
Cataract
Glaucoma
Refractive Error

Appendix C



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