Health Services & Outcomes Research

2014

HSOR@NHG

The evidence behind your decisions

FOREWORD

In 2014, strong support from NHG's senior management and commitment by stakeholders within and outside the NHG continued. This has paved the way for HSOR to realise one of its missions of providing the best evidence for decision making. Methodologies and analyses were developed to support planning of the various programmes, and programmes were evaluated for effectiveness with a focus on patient-centred outcomes.

HSOR is necessarily multi-disciplinary in its composition and team-oriented in approach because healthcare issues are multi-faceted. There are considerations of social factors, economics of choices, public service orientation, and data growth, against the backdrop of an inexorable increase in healthcare costs and tight operating capacity. Solutions varied from surveys to identify needs of patients that are not countable; analytical, geographical and visual where countable; and impartial where evidence was sought. There was a balance between pragmatic orientation to address the contextual real world questions of stakeholders, and finding space for publications, grants and awards where new knowledge was generated and applied.

The year saw the implementation of the various MOH priority areas in the six Regional Health Systems including that of NHG's Central Regional Health System. The department provided analyses to better understand our Central Region patients to support population health management. Frameworks were developed to evaluate programmes that addressed high-resource patients in primary and acute care. Various forecasts and predictions have informed planning and decisions. Work has also started on developing a measure of the overall health of the population in the Central Region.

During the year, the collaboration on evidence reviews of e- and mLearning and e- and mHealth with Lee Kong Chian School of Medicine and other international partners continued. NHG has also supported two HSOR researchers to undertake their PhDs - aptly aligned with the mission of building capacity and advancing knowledge in health services research.

This report is a compilation of work carried out during the year. Happy reading.

Prof Phillip Choo
Group Chief Executive Officer
National Healthcare Group

OUR VISION

To add years of healthy life to the people of Singapore through excellence in Health Services Research.

OUR MISSION

We will improve the quality of healthcare by providing best available evidence for decision making and knowledge translation; and building capacity and advancing knowledge in HSR.

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POPULATION HEALTH MANAGEMENT IN THE REGIONAL HEALTH SYSTEMS IN SINGAPORE

Dr Nakul Saxena, Alex You Xiaobin, Dr Zhu Zhecheng, Dr Sun Yan, Teow Kiok Liang, Dr Pradeep Paul George, Dr Eugene Fidelis Soh[1], A/Prof Benjamin Ong[2], Prof John Wong[2], Adj A/Prof Joe Sim[3], Foo Hee Jug[4], Adj A/Prof Chong Phui-Nah[5], Linus Tham[6], Dr Heng Bee Hoon, Prof Philip Choo[7]

[1] Tan Tock Seng Hospital
[2] National University Health System
[3] National University Hospital
[4] Alexandra Hospital
[5] National Healthcare Group Polyclinics
[6] National Healthcare Group, Corporate Development & Regional Health
[7] National Healthcare Group

BACKGROUND

This study describes the health service utilisation in three Regional Health Systems (RHS), namely the National Healthcare Group (NHG), the National University Health System (NUHS), and Jurong Health System (JHS), with an emphasis on the population at risk of high utilisation. The analyses will aid in the planning of healthcare interventions and will serve as a baseline for future comparison in the evaluation of programmes.

METHODS

Patient-related data (demographics, health services utilisation, chronic diseases, cost, and mortality) from various administrative databases and registries from the three RHSs (NHG – Tan Tock Seng Hospital (TTSH) and NHG Polyclinics (NHGP); NUHS – National University Hospital (NUH); and JHS – Alexandra Hospital (AH)) over 6 years (2008-2013) were extracted and merged.

Patients were segmented into "Frequent Admitters" (FA) (defined as having three or more inpatient admissions in the past 1 year from their last admission in 2013 to any regional hospital), "Chronic" (defined as having one or more chronic diseases listed in the Chronic Disease Management System (CDMS) database), and "Others" (defined as patients not having any chronic disease based on the CDMS list). This segmentation is mutually exclusive.

The health service utilisation across the three regional hospitals (TTSH, NUH and AH) and NHGP was studied and chronic disease distribution was assessed for the year 2013.

RESULTS

Table 1 shows that inpatient episodes per patient increased for all three hospitals while NHGP saw an increase in the number of outpatient visits in 2013 compared to 2008. Although the proportion of FAs in the three RHSs were small, they consumed a large amount of inpatient resources (Table 2). Chronic disease distribution showed that diabetes, hypertension and dyslipidaemia were the top chronic diseases among the FA and Chronic patients (Table 3).

Table 1 – Health service utilisation per patient in 2008 and 2013

	Utilisation (Episode/Attendance) per patient°					
	Inpatient		ED		Outpatient	
	2008	2013	2008	2013	2008	2013
AH	1.29	1.31 ↑	1.42	1.41 ↓	2.75	2.71 ↓
NUH	1.38	1.41 ↑	1.35	1.38 ↑	3.31	3.31
TTSH	1.38	1.45 ↑	1.37	1.43 ↑	3.66	3.41 ↓
NHGP	–	–	–	–	3.41	3.72 ↑

ED – Emergency department
°within same institution

Table 2 – Utilisation of inpatient services by Frequent Admitters in 2013

	Patient count		IP episode		Total LOS (days)	
	No. of FA ('000)	% all patients	No. of IP episodes ('000) by FA	% all IP episodes	LOS (days) by FA	% of LOS
JHS (AH)	1.87	2.6%	4.36	26.0%	31,474	31.7%
NUHS (NUH)	4.29	1.0%	14.80	27.1%	101,648	37.4%
NHG (TTSH & NHGP)	4.03	1.3%	13.60	29.6%	117,451	34.0%

LOS – Length of stay; IP – Inpatient

Table 3 – Chronic disease distribution for "Frequent Admitters" and "Chronic" patients in 2013

Chronic condition (CDMS)	Frequent Admitters			Chronic		
	AH	NUHS	NHG	AH	NUHS	NHG
(No. of patients)	1,865	4,290	4,033	22,158	148,272	137,091
Dyslipidaemia	75.3%	75.0%	80.1%	76.7%	78.4%	82.6%
Hypertension	72.6%	71.9%	77.8%	57.2%	64.3%	67.1%
Diabetes	51.2%	51.1%	54.1%	39.0%	34.9%	38.1%
Chronic kidney disease	47.1%	51.7%	56.7%	24.6%	22.2%	25.6%
Coronary heart disease	36.7%	42.9%	39.8%	14.0%	13.8%	14.8%
Heart failure	23.7%	26.9%	26.6%	4.4%	2.9%	3.2%
Atrial fibrillation	13.7%	18.0%	19.7%	3.8%	3.1%	3.6%
Stroke	23.6%	24.6%	29.2%	10.0%	8.0%	10.3%
TIA	3.1%	3.1%	3.5%	1.3%	1.3%	1.5%
Subarachnoid haemorrhage	0.2%	0.5%	0.4%	0.1%	0.1%	0.2%
COPD	12.3%	11.0%	15.0%	2.9%	1.9%	2.4%
Asthma	13.3%	12.6%	10.4%	13.0%	11.9%	8.5%
Osteoporosis	6.4%	6.6%	5.7%	3.6%	2.5%	3.1%
Hip fracture	5.6%	6.1%	7.3%	2.7%	0.9%	1.8%
Spine fracture	4.1%	3.8%	4.2%	1.4%	0.6%	1.0%

COPD – Chronic Obstructive Pulmonary Disease; TIA – Transient Ischemic Attack

CONCLUSION

As a first step to initiate population health management (PHM) strategies, it is essential to have a good understanding of the patients that the healthcare providers cater to. The goal of PHM is to keep the patient population as healthy as possible by providing integrated care. This not only lowers costs, but also redefines healthcare as an activity that encompasses far more than sick care.

Our study gave a detailed, data driven perspective of the health and health service utilisation of the population of Singapore. This information will help clinicians and decision makers design appropriate integrated care programmes for patients with the aim of minimising the expensive interventions, and covering the healthcare needs of all people across the spectrum of healthcare in Singapore.

DEVELOPMENT OF A REGIONAL HEALTH DATABASE FOR SEAMLESS POPULATION HEALTH MANAGEMENT IN SINGAPORE

Dr Pradeep Paul George, Palvannan R.K., Teow Kiok Liang, Alex You Xiaobin, Dr Zhu Zhecheng, Dr Sun Yan, Dr Nakul Saxena, Dr Eugene Fidelis Soh[1], A/Prof Benjamin Ong[2], Prof John Wong[2], Adj A/Prof Joe Sim[3], Foo Hee Jug[4], Adj A/Prof Chong Phui-Nah[5], Linus Tham[6], Dr Heng Bee Hoon, Prof Philip Choo[7]

[1] Tan Tock Seng Hospital
[2] National University Health System
[3] National University Hospital
[4] Alexandra Hospital
[5] National Healthcare Group Polyclinics.
[6] National Healthcare Group, Corporate Development & Regional Health
[7] National Healthcare Group

BACKGROUND

Understanding the health and health service utilisation of the population is critical for the Regional Health System's (RHS) population health management (PHM) initiatives. The RHS relational database is a collaborative effort to develop a national architecture for distributed healthcare utilisation data across diverse clinical systems with disparate data models. This study describes the development of an RHS database which would facilitate big data analytics for proactive PHM and health services research.

METHODS

The database, referred to as the RHS database, is a relational data warehouse which is a conglomeration of four data marts – Hospital operational data source (ODS), National Healthcare Group Polyclinic (NHGP) operational data source, Chronic disease management system (CDMS), and the Death registry. The database contains linked NHGP visit records, Specialist Outpatient Clinic visit records, hospital discharge abstracts from Tan Tock Seng Hospital (TTSH), National University Hospital (NUH) and Alexandra Hospital (AH), CDMS records, and mortality records from the Health Promotion Board. The data linkage process was conducted in four separate but interconnected steps using the unique identification number (NRIC) as the linking variable. The final database was an anonymised relational database with multiple interconnected tables that included patient demographics, chronic disease and healthcare utilisation tables.

RESULTS

Over 2.8 million patients had contact with the three RHSs (NHG, National University Health System (NUHS), and Jurong Health System (JHS)) from 2008 to 2013. Table 1 shows the patient demographics in the RHS database.

Table 1 – Patient demographics for the year 2013

RHS	NHG*	NUHS**	AH	ALL***
No. of patients	322,604	429,034	71,800	1,210,701
Age				
Mean Age (years)	48.1	40.7	46.3	42.9
<18	9.5%	17.1%	1.9%	13.4%
18-44	31.5%	37.2%	49.6%	37.9%
45-64	32.1%	29.4%	27.7%	29.9%
65-84	23.7%	14.8%	17.7%	16.8%
85+	3.1%	1.5%	3.1%	1.9%
Gender				
Female	51.1%	50.1%	39.8%	49.4%
Male	48.9%	49.9%	60.2%	50.6%
Race				
Chinese	75.5%	64.0%	58.8%	65.4%
Malay	7.5%	15.8%	11.8%	13.1%
Indian	9.5%	11.1%	14.2%	10.9%
Others	7.5%	9.1%	15.2%	10.6%
Mean no. of chronic diseases	1.2	0.9	0.9	0.9

* includes TTSH & Ang Mo Kio, Hougang, Toa Payoh Polyclinics
** includes NUH & Bukit Batok, Choa Chu Kang, Clementi, Jurong Polyclinics
*** includes all 3 hospitals and 9 NHG Polyclinics

The database facilitated the risk stratification of patients based on their past healthcare utilisation and chronic disease information. This database aids in understanding the cross-utilisation of healthcare services across the RHSs and the challenges of setting up a distinct geographical boundary for the RHSs. Table 2 shows the health services research questions addressed using the database.

Table 2 – Health services research questions addressed using the RHS database

1. Profile of patients in TTSH, JHS, NUH, NHGP by (a) demographics, (b) existing chronic diseases and comorbidities (primary and secondary diagnoses), (c) geographical distribution, (d) health service utilisation in primary care, emergency department, specialist outpatient clinic, day surgery and inpatient, and (e) cost from providers' perspective.
2. The extent of cross-utilisation by patients between the 3 RHSs (NHG, NUHS, JHS), especially among patients with chronic conditions.
3. Hospital-polyclinic affinity and its impact of patient flow and referrals.
4. Predictors of risk of hospital re-admission/death following discharge (re-admissions and death are competing risks).
5. To identify predictors of risk of hospital admission among polyclinic patients. For objectives 4 and 5, accurate death information will be obtained from the National Registry of Diseases Office (NRDO).

CONCLUSION

The RHS database has been developed to support the secondary use of administrative health data in health services research and proactive PHM.

PROGRESSION AND PREDICTION OF HIGH HEALTHCARE UTILISERS IN CENTRAL REGION

Dr Sun Yan, Palvannan R.K., Teow Kiok Liang, Dr Heng Bee Hoon

BACKGROUND

The identification of a patient's health risk level is the first important step towards planning, developing and implementing a personalised patient care plan by the health care provider, in collaboration with the patient. The patient-centred care plan may help the patient achieve better clinical outcomes and quality of life through prevention strategies, stabilising existing chronic disease conditions, and preventing acceleration to a higher risk category with higher costs.

It is a great challenge to accurately predict patients' risk level in as real time as possible using readily available information due to the heterogeneity of patients and the complexity of health and health care. Currently there is no readily implementable model that stratifies the patients' risk in the Central region of Singapore. A patient's actual risk level is usually measured by the resource utilisation in the health care system. Patients with higher number of hospital admissions were considered as higher risk.

This study aimed to develop and validate a prognostic model for stratifying patients' risk of readmitting to hospital within 1 year after discharge using routinely collected patient data.

METHODS

This was an observational cohort study using hospital administrative data and predictive modelling. All inpatients discharged from three hospitals (Alexandra Hospital, National University Hospital, and Tan Tock Seng Hospital) in 2012 were included. Patients who died in the hospital, died without re-admission, or were discharged against doctor's advice, and those who were not Singapore residents were excluded from the study. All patients were followed up for 1 year. Patients' data on demographics, Medifund or public assistance status, healthcare utilisation history, clinical diagnoses and comorbid conditions were extracted from the hospitals' administrative database. The primary outcome was patients who were high healthcare utilisers with three and more re-admissions in the following 1 year.

A model was developed and internally validated to identify patients at high risk of being high healthcare utilisers. The model was developed using 60.0% of the sample and validated using the remaining 40.0%. Significant predictors were entered into the model by stepwise logistic regression. Bayesian Information Criteria (BIC) was applied to select the best fit model.

RESULTS

Among high utilisers in the 2012 cohort, 20.0% died and 10.0% remained as high utilisers in the following 1 year. About 49.0% had no admission at all (Table 1).

Table 1 – Transition matrix of healthcare high utilisers for 2012 cohort

2012 cohort		Re-admission°° or death in 2013 (following 1 year)									
		0		1-2		3-4		5+		Death	
Risk Category°	n	Count	Row %	Count	Row %	Count	Row %	Count	Row %	Count	Row %
1-2	90,702	77,730	85.7%	7,670	8.5%	771	0.9%	232	0.3%	4,299	4.7%
3-4	9,608	5,276	54.9%	2,039	21.2%	453	4.7%	212	2.2%	1,628	16.9%
5+	4,059	1,423	35.1%	824	20.3%	364	9.0%	338	8.3%	1,110	27.3%
3-5	13,667	6,699	49.0%	2,863	20.9%	817	6.0%	550	4.0%	2,738	20.0%

°Number of admissions per year based on patients' last discharge date in 2012
°°Re-admission to any of the three hospitals

Risk of being a high utiliser was associated with utilisation history, age, diagnoses, comorbid conditions (renal disease, diabetes, chronic obstructive pulmonary disease, cancer, heart failure, rheumatologic diseases, and liver disease), Medifund or public assistance status, and admission type (emergency or elective).

In the final model, six important predictors were identified – past risk group, age, heart failure, number of Specialist Outpatient Clinic (SOC) conditions in preceding year, male gender, and stroke (Table 2). The c-statistics of the receiver operating characteristic (ROC) by the model using only the number of hospital admissions in preceding 1 year was 0.76 (95% CI: 0.76-0.78). The model could be easily written using an equation and integrated with the information system to make real time prediction.

Table 2 – Important predictors for frequent admissions/death the following year

Past risk group [LL]		B	Exp(B)	95% CI	
1-2y	1y			Lower	Upper
M	L	0.7	2.0	1.7	2.3
L	M	0.8	2.3	2.2	2.5
H	L	1.1	3.0	2.2	4.0
M	M	1.2	3.2	2.7	3.8
H	M	1.5	4.4	3.3	5.9
L	H	1.9	7.0	6.4	7.6
M	H	2.4	11.3	9.4	13.7
H	H	3.1	21.3	17.5	26.0
Age		0.1	1.0	1.0	1.1
Heart Failure		0.7	1.9	1.8	2.0
Number of SOC conditions in preceding year		0.1	1.0	1.0	1.1
Male		0.3	1.4	1.3	1.5
Stroke		0.2	1.2	1.2	1.3

Low (L) – 0-2 admissions; Moderate (M) – 3-4 admissions; High (H) – 5+ admissions
[ ] Reference group

CONCLUSION

The easily implementable proactive risk stratification model predicted patients' risk of being higher utilisers with good prediction accuracy. Well-structured interventions targeted on patients at different risk level might improve patients' outcomes and reduce hospital expenditure.

AN INTEGRATED AND COLLABORATIVE MODEL OF CARE FOR PATIENTS WITH HIP FRACTURE IN TAN TOCK SENG HOSPITAL (INTERIM RESULTS)

Dr Joseph Antonio D. Molina, William Chan Wai Lim[1], Dr Heng Bee Hoon, Li Ruijie, Dr Pradeep Paul George
[1] Tan Tock Seng Hospital, Department of Rehabilitation Medicine

BACKGROUND

From 1991 to 1998, there was a 40.0% increase in the number of patients admitted for hip fracture. This number is expected to rise two- to three-fold by 2025. The average cost of admission for hip fracture in 2004 was $9,348 and $11,502 for patients without and with co-morbidities, respectively. This was associated with a high 1-year mortality rate of between 14.0% and 36.0%. Gaps in care processes and care integration may lead to delays in surgery, transfers to community hospital as well as missing out on a low proportion of post-hip fracture patients who may require rehabilitation services after discharge from the hospital.

The aim of this programme was to deliver seamless integration of care from admission and treatment, to rehabilitation and post-discharge community services. In addition, the programme aimed to optimise patients' clinical outcomes and functional status through evidence-based clinical protocols and guidelines, as well as ensure timely access to services, treatments and follow-up, ultimately reducing inpatient length of stay, unplanned re-admissions and morbidity.

METHODS

Patients were eligible for inclusion into the programme if they were 60 years or older, and were admitted with acute fragility hip fracture (intertrochanteric, subtrochanteric, or neck of femur fracture). The intervention involved a set of integrated care pathways which span the various levels of care, from initial management at the emergency department (ED), inpatient admission for surgical or conservative management, inpatient or community hospital post-acute rehabilitation, and rehabilitation in the community for up to 1 year. The programme also involved optimised coordination of care from one level to the next to ensure quality and timeliness of care.

Results were compared with baseline data before programme implementation. Patients included in the programme were followed up from presentation at the ED up to 1 year post-fracture in the community. Data for the evaluation were extracted by a trained research assistant at each service level and were entered into a database. Results presented in this interim report are as of the second year of programme implementation.

RESULTS

As of the second year of programme implementation, there were 700 patients enrolled, with a median age of 81 years, 25.0% of whom were males. Table 1 presents the comparison between baseline and interim results.

Table 1 – Comparison of baseline and interim results

Indicator	Baseline	Interim
% admitted to the wards within 4 hours of arrival at the ED	43.0	55.0
% of patients deemed fit for operation who underwent surgery within 48 hours of admission	35.0	34.0
% started on therapy on the first post-operative day	60.0	92.0
% who underwent inpatient rehabilitation by the 6th post-operative day	41.0	53.0
% who underwent surgical management	80.0	80.0
% who met the criteria and were referred for day rehabilitation	9.0	78.0
% who were referred for day rehabilitation and completed the individualised programme at the day rehabilitation centre	29.0	79.0
Average length of stay of patients at the acute hospital for operated patients (days)	12.4	13.2
Average length of stay at inpatient rehabilitation (days)	30.7	29.0
Complication rate (%) Wound infections Pressure ulcers Urinary tract infection Venous thromboembolism	1.0 1.0 10.0 1.0	0.4 0.3 5.3 0.1
30-day re-admission rate (%)	1.0	1.0
1-year mortality rate (%)	14.6	14.0

CONCLUSION

Point estimates of the results suggested shorter times to admission, post-operative therapy and inpatient rehabilitation. There were more patients referred for day rehabilitation, and who completed the day rehabilitation programme. Rates of complications were lower after programme implementation.

STEPPING OUT — THE COMMUNITY HEALTH ENGAGEMENT PROGRAMME (INTERIM RESULTS)

Dr Joseph Antonio D. Molina, Dr Noor Hafizah Bte Ismail[1], Dr Heng Bee Hoon, Dr Ian Leong[1]
[1] Tan Tock Seng Hospital, Department of Continuing and Community Care

BACKGROUND

With the ageing of the Singapore population, the incidence of falls and its consequences will increase unless effective interventions are implemented. While hospital-based patient safety standards are in place to prevent falls among hospitalised patients, there is an equally pressing need for community-based preventive programmes.

This evaluation aimed to assess the effectiveness of the Stepping Out programme in preventing falls, improving overall physical performance, general health, well-being and falls efficacy, as well as reducing falls-related health service utilisation.

METHODS

Stepping Out is a 52-week programme for elderly residents of 1-/2-room public housing units. An initial assessment of the risk of falls forms the basis for assigning participants to the appropriate package of interventions, which include physical exercises, education, referrals to healthcare providers as necessary, as well as to community partners. The initial 3-month phase was supervised by nurses and physical therapists. This was followed by a 9-month maintenance phase, during which exercises were supervised by community volunteers. The programme was implemented in a phased manner, one block at a time. Currently in its fourth and final year of implementation, it aimed to enrol a total of 1,700 participants by end 2015.

The evaluation utilised a prospective cohort design. From the third year of implementation, eligible participants were invited to join the programme at least 1 year before receiving the intervention, during which data collected for that "baseline" year served as control data. Intervention data came from participants already receiving the intervention on a given year. Hence, the "exposed" group consisted of programme participants who were already receiving the intervention, whilst controls comprised those who have been invited to participate but who have yet to receive the intervention the following year.

RESULTS

The characteristics of the programme participants are shown in Table 1.

Table 1 – Baseline profile of programme participants

Profile	Intervention, No. (%) (n=1,500)	Control, No. (%) (n=286)	All participants, No. (%) (n=1,786)
Age	Mean=72.8, sd=7.82; Median=73.0	Mean=73.4, sd=7.31; Median=73.0	Mean=72.9, sd=7.75; Median=73.0
Male	347 (23.1)	71 (24.8)	418 (23.4)
Ethnicity			
Chinese	1,300 (86.7)	232 (81.1)	1,532 (85.8)
Malay	124 (8.3)	36 (12.6)	160 (9.0)
Indian	60 (4.0)	13 (4.5)	73 (4.1)
Eurasian	5 (0.3)	2 (0.7)	7 (0.4)
Others	10 (0.7)	3 (1.0)	13 (0.7)
Fell in the past year	342 (22.8)	62 (21.8)	404 (22.7)

Participants receiving the intervention had significantly better results for the 6-minute walk test, step test, falls efficacy score and life space assessment; there was also a significant improvement in SAFER score on follow-up for the intervention group. Although there was no significant difference in the results of the other physical performance and questionnaire-based assessments, none of the assessments showed better results for the control group.

After adjusting for demographics, baseline fall history and fall risk, baseline physical, and other questionnaire-based assessments, participants in the intervention group had significantly fewer falls during the follow-up year compared to controls (Figure 1 & Table 2).

Figure 1 – Rate of falls during follow-up

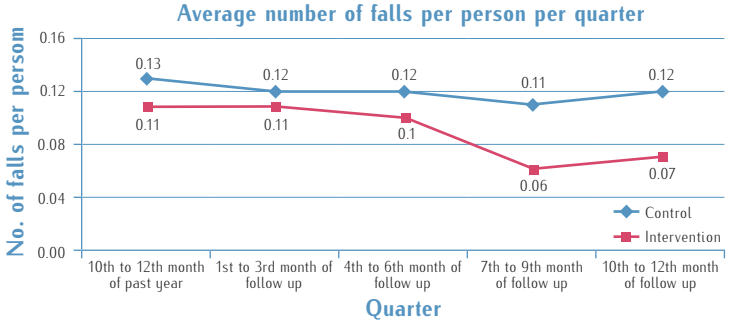


Table 2 – Generalised linear model of rate of falls during the follow-up year (N=1,031)

Independent variables	Odds Ratio	95% CI
Age	0.99	0.98, 1.01
Gender		
Male	1.34	1.06, 1.69
[Female]	–	–
History of fall in the past 1 year		
No	0.42	0.34, 0.52
[Yes]	–	–
Baseline falls risk profile		
High	0.86	0.59, 1.25
Moderate	0.95	0.71, 1.26
[Low]	–	–
Group		
Intervention	0.75	0.58, 0.97
[Control]	–	–

[ ] Reference group

Independent variables	Odds Ratio	95% CI
Falls efficacy score at baseline	0.88	0.81, 0.95
Life Space Assessment at baseline	1.01	1.01, 1.02
Timed-up-and-go at baseline	1.07	1.04, 1.11
Chair rise at baseline	0.96	0.93, 1.00
Step test at baseline		
Right	0.96	0.89, 1,01
[Left]	–	–
6-minute walk test at baseline	1.00	1.00, 1.00
Berg balance score at baseline	0.95	0.94, 0.97

[ ] Reference group

There was no significant difference between the intervention and control groups in terms of the proportion of participants with emergency department visits and hospital admissions for falls.

CONCLUSION

Results suggested that the Stepping Out programme improved physical performance and reduced the incidence of falls in the elderly. Findings should be more conclusive as more data become available.

EVALUATION OF THE STAR PALS PROGRAMME (INTERIM RESULTS)

Dr Joseph Antonio D. Molina, Dr Chong Poh Heng[1], Dr Chan Mei Yoke[2], Dr Koh Pei Lin[3], Kelvin Teo Wee Sheng
[1] HCA Hospice Care
[2] KK Women's and Children's Hospital, Haematology/Oncology Service
[3] National University Hospital, Division of Paediatric Critical Care & Division of Paediatric Haematology and Oncology

BACKGROUND

Globally, despite the evidence and a long history of an organised system of providing palliative care for adults, the care provided for children with life-threatening diseases has been far from adequate. Star PALS is a home-based paediatric palliative care programme implemented by HCA Hospice Care. The programme offers a variety of services to patients aged 19 years and below who suffer from life-limiting medical conditions. Services include pain and other symptom management, caregiver training, psychosocial and emotional support, respite for caregivers, equipment loans, allied health services, care coordination, advance care planning, end-of-life care at home, as well as bereavement care.

For this phase of the evaluation, the objectives were: (1) among patients who have died, to determine if there was a difference in the proportion of time spent at home versus hospital, and the number of unplanned hospital admissions between patients enrolled in Star PALS and those who received standard care up to 1 year before death; and (2) for patients in the programme, to describe the patients' health-related quality of life (HRQoL) and to describe the caregivers' level of burden during the first year of participation in the Star PALS programme.

METHODS

Patients were eligible for enrolment into the programme if they were 19 years and below, and have a medical condition which made them unlikely to survive to adulthood. They were enrolled into the programme either through self-referral, referrals from partner paediatric units at tertiary centres, and through referrals from primary physicians or general paediatricians.

For Objective 1 (proportion of time spent at home and number of unplanned admissions), the evaluation utilised a retrospective cohort design. Outcomes were compared between Star PALS patients who have died and patients who were not enrolled in Star PALS who have likewise died. Data on outcomes were collected up to 1-year prior to death.

For Objective 2 (caregiver burden and HRQoL), the evaluation utilised a single group study with assessments conducted prospectively at 0-, 3-, 6- and 12-months from enrolment. HRQoL was assessed using the Health Utilities Index (HUI) while caregiver burden was assessed using the Zarit Burden Interview (ZBI).

RESULTS

Objective 1 (number of unplanned admissions and proportion of time spent at home):
There were 51 Star PALS patients and 134 controls included in this interim analysis. Star PALS patients were older (10.02 vs. 1.75 years) and had a greater proportion of males (68.6% vs. 49.3%). The mean duration of follow-up for Star PALS patients and controls was 118 and 158 days, respectively.

Preliminary results showed that there was no significant difference in the number of admissions at each quarter of follow-up between Star PALS patients and controls (Table 1).

Table 1 – Mean number of admissions

Quarter before death	Star PALS		Control		95% CI of the difference
	N	Mean no. of admissions	N	Mean no. of admissions	
1st	51	1.08	134	0.84	-0.68, 0.20
2nd	26	0.77	62	0.97	-0.42, 0.81
3rd	11	0.82	52	1.19	-0.77, 1.51
4th	6	0.67	49	0.86	-0.94, 1.32

There was no significant difference in the proportion of time spent at home between Star PALS patients and controls (Table 2).

Table 2 – Proportion of time spent at home

	Star PALS (N=6)	Control (N=49)	95% CI of the difference
Proportion of time spent at home among patients followed-up for 4 quarters before death	0.91	0.83	-0.24, 0.09

Objective 2 (caregiver burden and HRQoL):
As of September 2014, there were 13 respondents who completed the ZBI and HUI, 3 of whom had at least one follow-up assessment. Average age of patients was 9.0 years; 70.0% were female.

Due to the small sample size, a test of significance was not conducted. At baseline, 69.2% of the respondents had mild to moderate burden and 15.4% had moderate to severe. On follow-up, 50.0% of the respondents had mild to moderate burden with the rest having little or no burden (Table 3).

Table 3 – Caregiver burden

Interpretation	No. (%)	
	Baseline	Follow-up
No. of records included in the analysis	13	4
Little or no burden	2 (15.4)	2 (50.0)
Mild to moderate burden	9 (69.2)	2 (50.0)
Moderate to severe burden	2 (15.4)	0 (0.00)

Though no tests of significance were conducted, results suggested a greater proportion of patients with more severe levels of sensation, mobility, cognition and self-care (based on HUI2) and vision, speech, ambulation, dexterity and cognition (based on HUI3) on follow-up compared to baseline. Results also showed a greater proportion of patients reported improved emotion and reduced pain on follow-up.

CONCLUSION

Bearing in mind the small sample size, and despite the non-significant differences in quarterly admissions between groups, results showed that Star PALS patients had fewer admissions in the second, third and fourth quarters before death, as well as a greater proportion of time spent at home.

Although no tests of significance were conducted, preliminary findings of caregiver burden and HRQoL suggested possible beneficial effects of the intervention with respect to caregiver burden, patients' emotion and pain control. Differences in results across specific quality of life attributes should be explored further in subsequent analyses in light of the observation that the intervention may be more effective for some attributes, and less effective for others.

ANNUAL ALL-CAUSE MORTALITY RATE OF DIABETES PATIENTS IN A SINGAPORE CHRONIC KIDNEY DISEASE REGISTRY

Dr Gary Ang Yee, Dr Heng Bee Hoon, Adj Asst Prof Adrian Liew Seng Teck[1], Adj A/Prof Chong Phui-Nah[2]
[1] Tan Tock Seng Hospital, Department of Renal Medicine
[2] National Healthcare Group Polyclinics

BACKGROUND

Chronic kidney disease (CKD) is defined as either functional or structural kidney damage or an estimated glomerular filtration rate (GFR) of <60mL/min per 1.73m^2 for at least 3 months. It can be divided into five stages from Stage 1 to Stage 5, with Stage 3 further subdivided into Stages 3A and 3B depending on the estimated GFR.

The prognosis of diabetes patients with CKD has been guarded because epidemiological data has shown that all-cause mortality increases as kidney function decreases. The aims of the study were to estimate the annual mortality rate of these patients by CKD stages, and to identify predictors of mortality.

METHODS

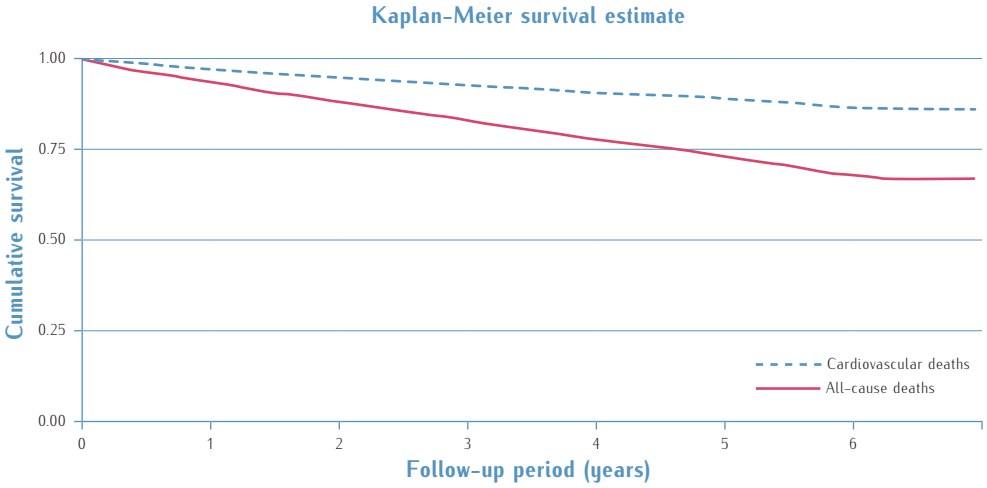
This was a retrospective cohort study of Stage 3A and above CKD patients from the National Healthcare Group CKD Registry from January to December 2007. Only patients with diabetes were included in the study. Death data was obtained from the National Registry of Disease Office. Patients were followed up till November 2013, and the event of interest was death from all causes.

Univariate followed by multivariate Cox's proportional hazards regression were used to assess associations, measured as hazard ratios (HR), between predictors and all-cause deaths.

RESULTS

Over a median follow-up period of 6.0 years (range 0-6.9 years), 985 out of 3,008 (32.8%) patients died. Of those who died, 363 (36.9%) died of cardiovascular causes. The Kaplan-Meier survival curves are shown in Figure 1. The annual mortality rate was 64.1 per 1,000 individuals (95% CI: 60.2-68.3) and the mortality rate increased with severity of disease (Stage 3A - 37.0, Stage 3B - 57.5, Stage 4 - 98.3, and Stage 5 - 198.5). Predictors associated with 5-year mortality were presence of albuminuria, increasing age, male gender, and increasing CKD stages.

Figure 1 – Kaplan-Meier survival estimate



CONCLUSION

We estimated the annual all-cause mortality rate for diabetes patients with CKD by CKD stages and identified predictors of all-cause mortality. This study affirmed the guarded prognosis of these patients and an urgency to act to prevent progression to later stages of CKD.

PROJECTS

ORGANISATION & DELIVERY OF SERVICES

QUANTIFYING PATIENT FLOW AND UTILISATION WITH PATIENT FLOW PATHWAY AND DIAGNOSIS OF AN EMERGENCY DEPARTMENT IN SINGAPORE

Dr Meng Fanwen, Dr Ooi Chee Kheong[1], Christopher Soh Kok Keng[1], Teow Kiok Liang, Palvannan R.K.
[1] Tan Tock Seng Hospital, Emergency Department

BACKGROUND

Emergency department (ED) utilisation has been growing rapidly, resulting in overcrowding, consult or admission delays, and increased staff burnout. In the past decade, a number of publications related to ED resource utilisation have been published to describe operational strategies for managing patient flow. Many studies have examined factors associated with ED utilisation using regression-based statistical models. The factors include frequent visits, patient boarding, non-emergency attendances, insured or lack of insured or homeless patients, and access to primary care. Time-series analysis was sometimes used to forecast ED visits. In addition to statistical modelling approaches, a number of studies simulated patient flows using operations research methods such as queueing theory and discrete event simulation.

There is a paucity of studies quantifying estimated changes in resource utilisation due to changes in patients' diagnoses. In particular, few studied how different diagnosis groups impacted workload and patient flow pathways crossing key functional areas within ED. This information is important for human resource and capacity planning. The aim of this study was to fill this gap.

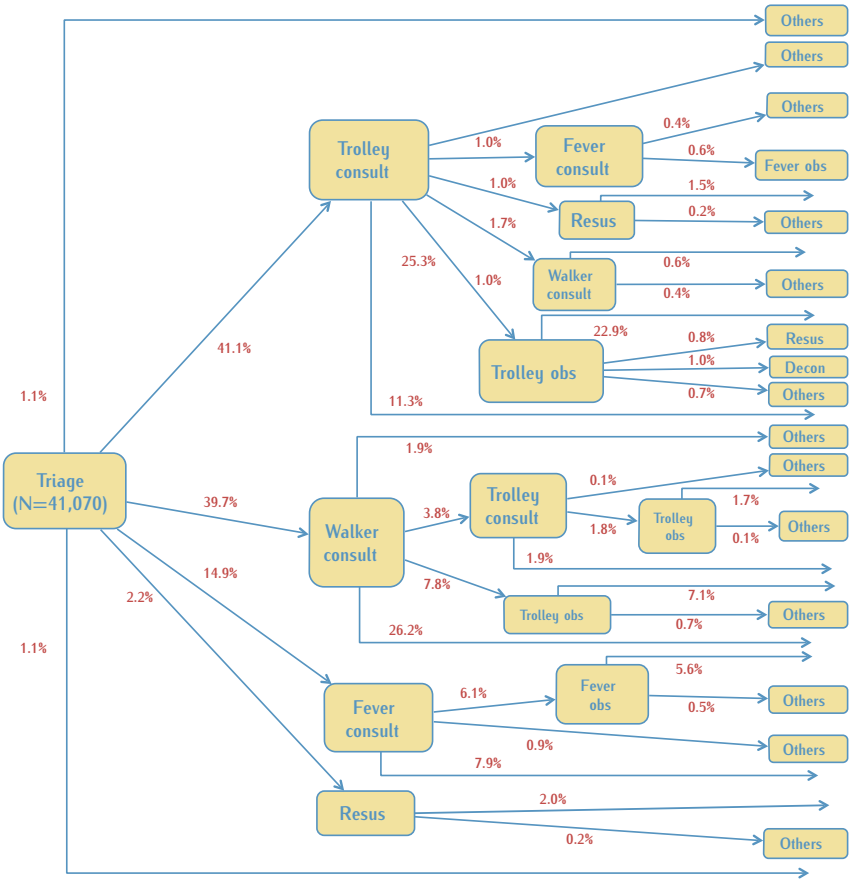
METHODS

When patients arrive at ED, nurses will triage them. Doctors will assess them in consultation rooms. After consultation, patients may proceed to observation rooms, or leave ED. We studied the key functional areas in ED – triage, consult, resuscitation, ED observation, fever observation, and fever isolation. A patient touch point was defined as the area when the patient arrives at that location. Changes to touch points were captured when staff updates patients' locations in our ED information system. We first mapped patient flow pathways across these key functional areas. We then computed the workload of these functional areas stratified by diagnosis groups. Using a deterministic mathematical model, we estimated the changes in workload using impact analysis.

RESULTS

We analysed records of 41,070 patients from October to December 2012, who attended the ED of Tan Tock Seng Hospital. 251 patient flow pathways were identified. Figure 1 illustrates 28 pathway patterns which were broadly representative of all identified patient flow pathways. Pathways ending with an arrow indicated patients who exited from ED, while those ending with "others" meant there were more subsequent touch points which have been truncated.

Figure 1 – Patient flow pathway at ED



There were 107 diagnosis groups, with different utilisation patterns. In particular, patients with "symptoms, signs and ill-defined conditions" topped the diagnosis groups, accounting for 20.0% of the total ED visits. Impact analysis showed that the various diagnosis groups had different degrees of impact on the functional areas, as illustrated in Table 1. For example, if patients with "acute respiratory infections" were to increase by 10.0%, the utilisations at Fever consult area and the Fever observation room would increase by 3.7% and 1.4% respectively.

Table 1 – Impact on area utilisation of 10.0% increase in volume in the top 7 diagnosis groups

ICD code	Present volume	Incremental rate								
		Triage	Trolley	Trolley Obs	Walker	Fever	Fever Obs	Resus	Decon	Fever Iso
780–789	19.6%	2.0%	2.5%	2.9%	1.7%	1.3%	1.6%	1.3%	2.4%	1.7%
460–466	6.9%	0.7%	0.1%	0.1%	0.2%	3.7%	1.4%	0.0%	0.0%	0.9%
920–924	4.4%	0.4%	0.4%	0.2%	0.7%	0.1%	0.0%	0.1%	0.1%	0.1%
840–848	4.3%	0.4%	0.2%	0.2%	0.8%	0.1%	0.0%	0.0%	0.1%	0.0%
555–558	4.3%	0.4%	0.5%	0.6%	0.5%	0.2%	0.2%	0.2%	0.3%	0.2%
680–686	3.2%	0.3%	0.2%	0.4%	0.6%	0.1%	0.1%	0.1%	1.4%	0.1%
490–496	3.1%	0.3%	0.1%	0.0%	0.0%	1.6%	2.2%	0.5%	0.0%	0.5%

Trolley Obs – Trolley Observation; Fever Obs – Fever Observation;
Resus – Resuscitation; Decon – Decontamination; Fever Iso – Fever Isolation

CONCLUSION

Our analysis of ED patient records demonstrated the complexity of patient flows. We showed that diagnosis groups would have different workload impact on ED functional areas. The study suggests an introductory reference for emergency care and treatment.

PIONEER POLYCLINIC PATIENT FLOW SIMULATION

Dr Zhu Zhecheng, Dr Karen Bek Siew Lian[1]
[1] National Healthcare Group Polyclinics, Operations

BACKGROUND

Pioneer polyclinic is the tenth polyclinic by the National Healthcare Group Polyclinics (NHGP). A new care model and service process will be applied in Pioneer polyclinic, e.g., team-based consultation. The study aimed to inform on the resources needed in Pioneer polyclinic via modelling and simulation.

METHODS

The whole Pioneer polyclinic workflow was modelled at two levels:

Macro level
- Overall workload projection of Pioneer polyclinic based on previous study
- Detailed workload breakdown based on Jurong Polyclinic's historical data

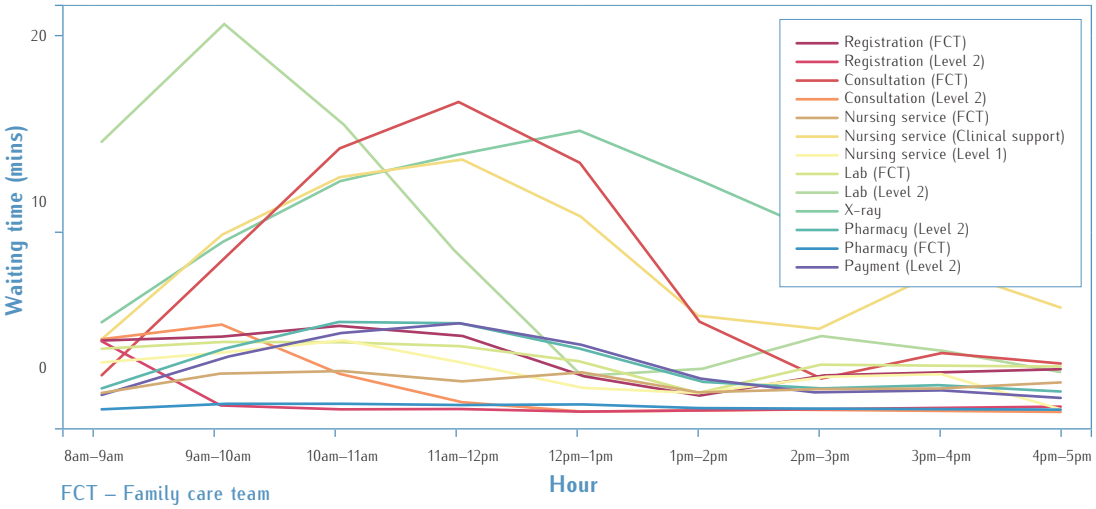
Micro level
- A discrete event simulation (DES) model was constructed to simulate patient-level flow from registration to leaving Pioneer polyclinic
- Waiting time and resource utilisation was evaluated at individual station level
- Different what-if scenarios were considered

RESULTS

Raw data from August 2013 to July 2014 was used to estimate simulation parameters. Two future scenarios for 2017 and 2030 were considered. Within each year, weekday and weekend scenarios were considered. Another scenario variation was whether team care service of Pioneer polyclinic would be available on weekends. Hence, a total of eight scenarios were considered.

Figure 1 lists the simulation results of a weekday scenario with team care service available on weekends in the year 2017. It shows the 50th percentile waiting time broken down by hour of each station considered in the whole workflow.

Figure 1 – Hourly distribution of 50th percentile waiting time



FCT – Family care team

CONCLUSION

Such a study would help decision makers in NHGP test different what-if scenarios and estimate resources needed to achieve certain performance indicators.

QUEUEING DISCIPLINES APPLIED ON OUTPATIENT PHARMACY DISPENSING

Teow Kiok Liang, Wee Chuan Hing[1], Angeline Chiam[1]
[1] National University Hospital, Pharmacy Department

BACKGROUND

With an automated picking and packing dispensing system in place, the National University Hospital (NUH) outpatient pharmacy has been looking at how to further fine-tune the system to improve waiting time, without adding resources. In queueing theory, given the same demand and capacity, "partitioning" generally results in longer waiting time. On the other hand, practicing the rule of "shortest-job first" will reduce overall waiting time (e.g. compared to first-in-first-out where the earliest request is assigned first), though with the possibility of "starving" the longer jobs.

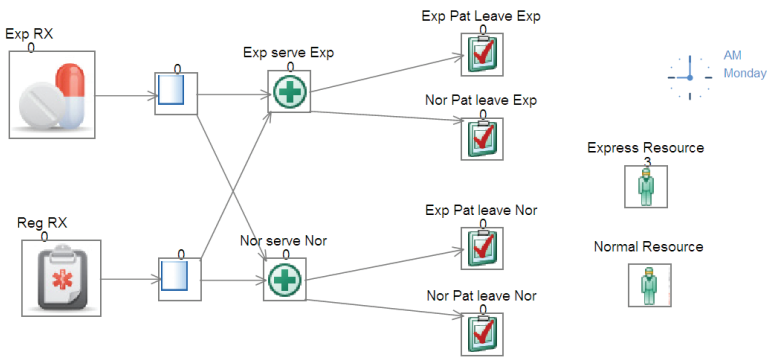
In supermarkets, there are often "express" counters set up for customers with few items. This is an instance of "partitioning" and having shortest-job first principle. In this study, we used queueing principles and simulation models to study the effect of allocating different number of dispensing counters to normal and express queues.

METHODS

We built a discrete event simulation model to mimic the dispensing process (Figure 1). The model starts from ready to be dispensed prescriptions, to end of prescription. The prescriptions from the patients were categorised into short and long groupings. The dispensing counters were also divided into express and regular counters. We ran various scenarios with the dispensing counters:

a) "Dedicated" scenario: Taking jobs from assigned groups of prescriptions only (i.e., express to short, regular to long)
b) "Merge" scenario: Taking jobs regardless of prescriptions' groupings
c) "Flexible" scenario: Taking jobs from their primary assignment, but also taking jobs from the other groupings when the counters are available. For this scenario, we also performed sensitivity analysis with different number of counters assigned to express counters, while keeping the total counters constant.

Figure 1 – Discrete event simulation of express and regular queues



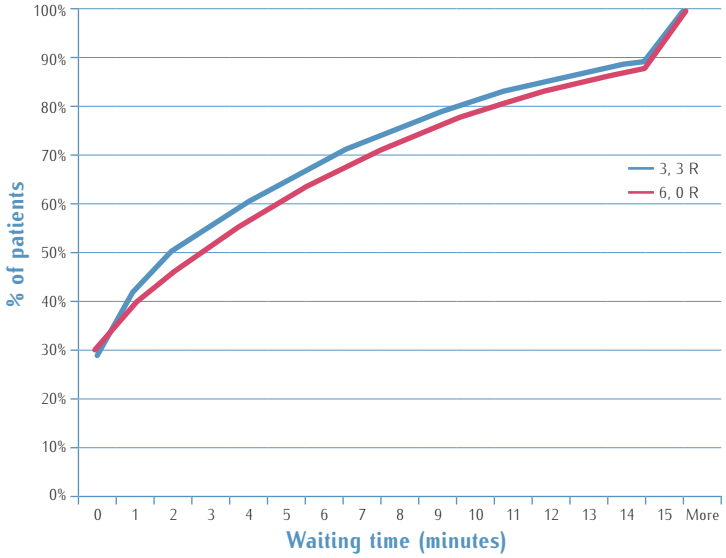
RESULTS

The simulation results showed that the dedicated scenario had the worst performance, while the flexible scenario had the best (Table 1). The results improved with more counters assigned to express queues, with little impact on the regular (longer) prescriptions (Figure 2).

Table 1 – Average waiting time for the various scenarios

Average waiting time (min)	Dedicated	Merge	Flexible (express counters, regular counters)				
			(2+4)	(3+3)	(4+2)	(5+1)	(6+0)
Express	2.4	-	3.2	2.0	1.6	1.3	1.1
Regular	12.5	-	4.9	5.5	5.7	5.9	6.0
Overall	5.5	4.4	3.7	3.1	2.9	2.7	2.6

Figure 2 – Percentage of regular patients waiting within "x" minutes for (3,3) and (6,0) configurations



CONCLUSION

It is important that the dispensing counters have the flexibility to switch between the two prescriptions' groups when they are available. With this flexibility, we showed that having express counters will reduce the overall waiting time, without significantly starving the regular prescriptions.

IMPACT OF HIGHER BED OCCUPANCY RATE ON 3-DAY RE-ATTENDANCE RATE AT THE EMERGENCY DEPARTMENT

Dr Sun Yan, Dr Heng Bee Hoon, Dr Tay Seow Yian[1], Dr Kelvin Bryan Tan[2]
[1] Tan Tock Seng Hospital, Emergency Department
[2] Ministry of Health, Policy Research & Economics Office

BACKGROUND

High bed occupancy rate (BOR) is often used as an indicator of productivity for hospitals, and can reduce patient comfort and privacy. Hospitals with BOR of above 85.0% are generally considered to have bed shortages. Little attention has been paid to the impact of these shortages on patients' outcomes, especially on its impact on the 3-day unplanned re-attendance rate at the emergency department (ED).

Re-attendance at the ED is monitored to determine the level of appropriate care given to patients during their first ED visit. One common indicator used to measure the level of care is unscheduled return to the ED within 72 hours prior to the last visit as it may represent premature discharges from the first ED visit, missed diagnosis, or some failure in the treatment or discharge plan. In order to address the gap, this study aimed to explore the association between BOR and 3-day unplanned ED re-attendance rate in public hospitals in Singapore.

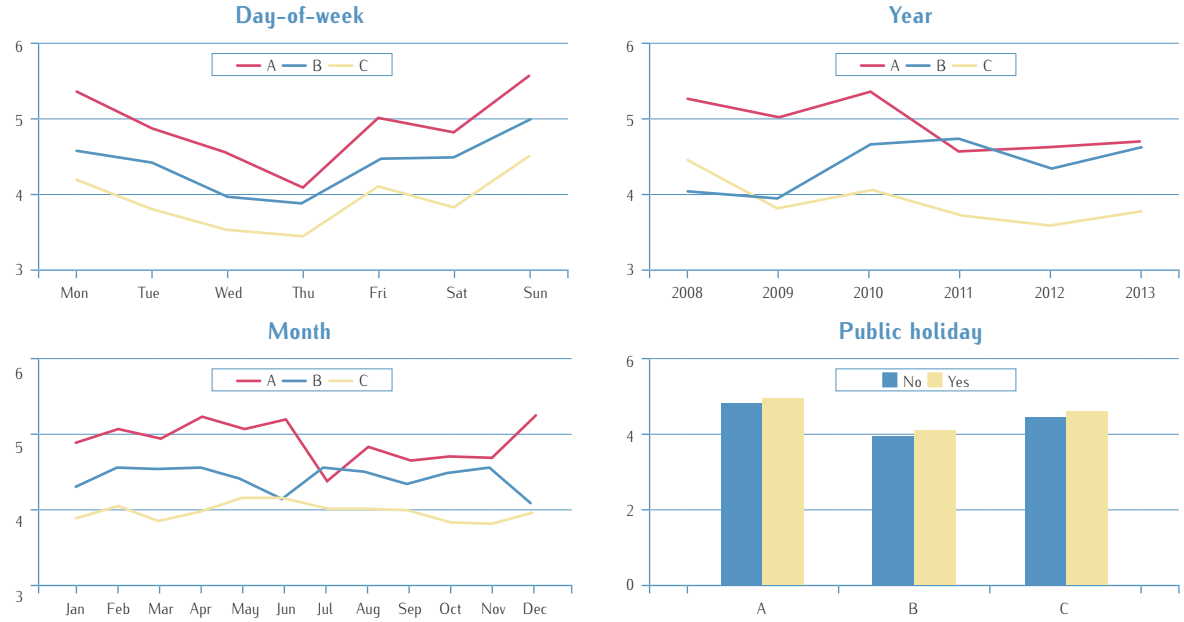
METHODS

This was a time-series study using retrospectively collected summarised daily data. The primary outcome was the 3-day unplanned re-attendance rate due to any reason. Data from 2008 to 2013 were extracted from three public hospitals in Singapore. Variables collected included first ED visit date (day of week, month and year), public holiday (yes or no), re-attended at ED within 3 days (yes or no), daily average BOR, and ED admission rate, median, and 95th percentile bed waiting time on the first ED visit day. Generalised linear regression was applied to study the association between the ED re-attendance rate and other factors. The subgroup analysis by hospital was also applied to study the heterogeneity among hospitals.

RESULTS

There were a total of 2,190 time points for each hospital over the 6-year period. The average 3-day unplanned ED revisit rate was 4.4% (SE=0.21%). After controlling for other covariates, the factors significantly associated with 3-day ED re-attendance rate were hospital, day of week, BOR, admission rate, and a slightly decreasing time trend. Thursday had the lowest re-attendance rate, while Sunday had the highest re-attendance rate (Figure 1). Patients who visited ED on the dates with higher BOR or lower ED admission rate were more likely to revisit ED within 3 days.

Figure 1 – 3-day ED re-attendance rates of Hospitals A, B, and C (%)



By subgroup analysis, the associations between the ED re-attendance rate and BOR, ED admission rate, or bed waiting time varied with hospitals' available resources and their operation efficiency in ED and inpatient wards. There was a slightly decreasing time trend on the ED re-attendance rate in Hospitals A and B, and a slightly increasing trend in Hospital C. There was no evident pattern on month. In Hospitals A and B, higher BOR was associated with ED re-attendance rate, but not for Hospital C. In Hospitals A and C, higher ED admission rate was associated with lower ED re-attendance rate. Bed waiting time and public holiday did not affect the ED re-attendance rate (Table 1).

Table 1 – Adjusted associations between 3-day ED re-attendance rate and the factors by hospital

Parameter	Hospital A			Hospital B			Hospital C		
	Exp(B)	95% CI Lower	Upper	Exp(B)	95% CI Lower	Upper	Exp(B)	95% CI Lower	Upper
Day of Week [Thu]									
Mon	3.14	2.24	4.40	1.92	1.49	2.47	1.99	1.60	2.47
Tue	2.11	1.51	2.96	1.34	1.05	1.71	1.68	1.36	2.07
Wed	1.50	1.08	2.10	1.04	0.82	1.33	1.04	0.85	1.29
Fri	2.56	1.83	3.58	2.07	1.61	2.66	1.64	1.32	2.02
Sat	2.23	1.59	3.13	1.78	1.36	2.32	1.71	1.38	2.11
Sun	4.00	2.82	5.67	2.95	2.26	3.85	3.03	2.39	3.85
Month [Jan]									
Feb	1.21	0.77	1.88	1.18	0.85	1.63	1.27	0.96	1.68
Mar	1.14	0.74	1.76	0.96	0.70	1.32	1.25	0.96	1.64
Apr	1.42	0.92	2.20	1.12	0.81	1.54	1.29	0.98	1.69
May	1.22	0.79	1.88	1.29	0.94	1.78	1.12	0.85	1.47
Jun	1.39	0.90	2.17	1.37	0.99	1.89	0.83	0.63	1.09
Jul	0.64	0.41	1.00	1.24	0.90	1.71	1.19	0.91	1.56
Aug	1.05	0.68	1.63	1.28	0.93	1.76	1.08	0.82	1.42
Sep	0.92	0.59	1.44	1.25	0.90	1.72	0.97	0.73	1.27
Oct	0.96	0.62	1.49	1.01	0.74	1.40	1.10	0.84	1.44
Nov	0.94	0.61	1.47	1.02	0.74	1.41	1.16	0.88	1.53
Dec	1.60	1.03	2.49	1.30	0.94	1.79	0.72	0.55	0.95
Public holiday	1.01	0.61	1.68	1.26	0.86	1.84	1.04	0.75	1.43
BOR	1.01	1.00	1.02	1.02	1.00	1.04	1.01	0.99	1.02
Admission rate	0.97	0.95	1.00	0.99	0.97	1.00	0.99	0.98	1.00
BWT_95th percentile	1.13	0.98	1.29	1.03	0.99	1.08	0.99	0.97	1.01
Time trend	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

[ ] Reference group BWT – Bed waiting time

CONCLUSION

A study using time-series data was applied to study how higher BOR affected the 3-day unplanned ED re-attendance rate in Singapore. A strong weekly effect was observed. The effect of higher BOR on re-attendance rate varied with each hospital. There was no evidence to support the hypothesis that higher BOR deteriorated the service quality in ED.

PREDICTING PATIENT'S NEED FOR INTENSIVE CARE UNIT ADMISSION IN THE EMERGENCY DEPARTMENT

Dr Sun Yan, Chong Wai Fung, Dr May Me Thet, Dr Tay Seow Yian Tay[1], Dr Heng Bee Hoon
[1] Tan Tock Seng Hospital, Emergency Department

BACKGROUND

Deciding which patients should be admitted to the intensive care unit (ICU) is a daily problem for ICU physicians. They face a challenging job in risk stratifying patients and in deciding whether to refer patients to the ICU. There are no well-defined guidelines for ICU admission. Little is known about the information available for triage or the outcomes of patients who refused ICU. On the other hand, predicting patients' needs for ICU admission early can help facilitate patient flow from the emergency department (ED) to ICU, and better prepare and allocate resources needed for patients. This might help reduce mortality and improve clinical outcomes.

To address the gap, this study aimed: 1) to identify factors associated with physician's decision to ICU admission within 24 hours of presenting at the ED resuscitation room; and 2) to develop and validate a prognostic model to predict patient's need for ICU admission in 24 hours.

METHODS

This was a predictive modelling study using retrospectively collected data extracted from the hospital information system. Patients who visited ED and were treated at the resuscitation room from September 2010 to March 2012 were included in the study. Patients who died without ICU admission within 24 hours were excluded. The primary outcome was admission to ICU within 24 hours of presenting at the ED resuscitation room.

Variables included were demographics (age, gender, and ethnic group), mobility, arrival mode, and co-existing chronic diseases, clinical parameters and vital signs. Chi-square tests were used to study the association between the selected possible risk factors and the need for hospital admission. Logistic regression was applied to develop the prediction model. Data were split for derivation (60.0%) and validation (40.0%). The receiver operating characteristic (ROC) and goodness-of-fit test were applied on the validation dataset to evaluate the model.

RESULTS

Out of 5,298 patients who were treated in the ED resuscitation room, 4,623 were included, and eventually 9.3% were admitted to the ICU within 24 hours. In the developed predictive model, pH value, heart rate, activity of daily living (ADL), urea, moderate or severe liver disease, and age were most predictive of the need for ICU admission (Table 1). The c-statistics of the ROC curve was 0.84 (0.83-0.86). The sensitivity of the model was 64.7%, and the specificity of the model was 94.5% (Table 2). The non-significant goodness-of-fit test showed that the predicted patients' ICU admission risks fit their actual status well.

Table 1 – Predictors and their regression coefficients

	B	Exp (B)	95% CI of Exp (B) Lower	Upper
ADL [Independent]				
Partial dependent	-1.7	0.2	0.1	0.6
Totally dependent	-2.6	0.1	0.0	0.3
Heart rate [70-109]				
110-139 or 55-69	0.4	1.5	1.1	2.0
140-179 or 40-54	1.3	3.6	2.4	5.4
>179 or <40	2.3	10.0	5.1	19.5
pH [7.35-7.45]				
<7.35	0.6	1.9	1.2	3.0
>7.45	0.5	1.7	0.6	4.8
Urea [Normal]				
Abnormal	0.7	1.7	1.3	3.1
Age group [75+]				
<45	0.6	1.9	1.3	2.7
45-54	0.5	1.7	1.2	2.4
55-64	0.8	2.1	1.5	3.0
65-74	0.5	1.6	1.2	2.3
Moderate/severe liver disease [No]				
Yes	1.6	4.9	2.5	9.5

[ ] Reference category

Table 2 – Predicted ICU admission risk and actual admission status

		Predicted ICU admission risk					
		No			Yes		
		Count	Row %	Col %	Count	Row %	Col %
Actual ICU admission	No	3,789	90.4%	94.5%	402	9.6%	51.3%
	Yes	220	36.6%	5.5%	381	63.4%	48.7%

CONCLUSION

A model for predicting the need of ICU admission among all-cause ED patients was developed and validated using routinely collected data. The model might assist ED doctors in decision making and identify patients for early ICU admission planning and resource allocation, and thus potentially improve patients' outcome.

PREDICTING RE-ATTENDANCE OF TAN TOCK SENG HOSPITAL EMERGENCY DEPARTMENT PATIENTS WITHIN 72 HOURS

Kelvin Teo Wee Sheng, Dr Meng Fanwen, Teow Kiok Liang, Dr Ooi Chee Kheong[1], Dr Tay Seow Yian[1]
[1] Tan Tock Seng Hospital, Emergency Department

BACKGROUND

The proportion of emergency department (ED) patients who returned within 72 hours is often an indicator for quality of care, and should be reduced as much as possible. Several factors may be possible causes for unscheduled emergency return visits. Identifying these factors would be critical in decreasing the number of unnecessary visits in this group.

The primary aim of this research was to study if there were parameters that could help to reduce ED re-attendance at the point of discharging. The secondary aim was to see if some prediction approaches would perform better than other approaches.

METHODS

We collected ED attendances from Tan Tock Seng Hospital (TTSH) from 2011 to 2013. The index cases excluded those admitted, death, absconded, cancelled and recall cases. Cases admitted to the Emergency Diagnostic and Therapeutic Centre (EDTC), a short-stay ward in TTSH, were not counted as re-attendances. From here, we tagged those who returned to ED within 3 days as re-attendances.

Literature and clinicians' inputs were sought to select variables as predictors. We featured about 100 variables including patients' demographics, diagnosis and patient acuity, chief complaints, selected laboratory tests, summarised vital signs (average, range, last measured and standard deviation), and medical history. We also coded if the patients ever had social issues, though this might not have been documented extensively. The data was partitioned into training and testing sets.

We used three approaches (logistic regression, decision tree, and discriminant analysis mixed integer programming (DAMIP)) for prediction, where each approach included a few sub-models. DAMIP is an optimisation-based discriminant analysis to identify a classification rule with relatively small subsets of factors that can be used to predict patient return within 3 days.

RESULTS

Overall, 4.6% of attendances were followed by a revisit to ED within 3 days. This figure remained stable across the years. While there existed significant predictors like age, presence of social issues, certain chief complaints, and principal diagnosis, all three approaches did not produce good results in terms of sensitivity and specificity (Tables 1–3). Depending on the cut-off, a higher sensitivity could only be achieved at the expense of more false positives. For instance, DAMIP could produce about 40.0% sensitivity with 74.0% specificity.

Table 1 – Prediction results of patient returning to ED within 72 hours using DAMIP approach

No. of features selected	Training set: 109,674 (return: 5,106)			Testing set: 219,059 (return: 10,065)		
	Overall	Sensitivity (return accuracy)	Specificity (no return accuracy)	Overall	Sensitivity (return accuracy)	Specificity (no return accuracy)
13	83.4%	29.3%	86.0%	83.3%	29.3%	85.9%
12	72.5%	41.1%	74.1%	72.5%	40.4%	74.0%
11	72.7%	40.6%	74.3%	72.6%	40.2%	74.1%
10	72.7%	40.6%	74.3%	72.7%	40.0%	74.3%
9	72.9%	40.4%	74.4%	72.8%	39.8%	74.4%

Table 2 – Prediction results of patient returning to ED within 72 hours using logistic regression

Hosmer-Lemeshow test C-statistics of ROC curve Predictive accuracy	Training set: 216,239 (return: 10,067) P = 0.000 0.67			Testing set: 120,113 (return: 5,452) P = 0.000 0.66		
	Overall	Sensitivity	Specificity	Overall	Sensitivity	Specificity
70% cutoff	95.4%	1.7%	99.9%	95.5%	1.0%	99.9%
50% cutoff	95.5%	4.6%	99.9%	95.5%	2.4%	99.9%
20% cutoff	95.2%	11.9%	99.3%	95.2%	7.2%	99.4%
10% cutoff	92.7%	18.5%	96.3%	92.4%	14.1%	96.1%
5% cutoff	71.2%	51.6%	72.2%	69.9%	51.0%	70.8%

Table 3 – Prediction results of patient returning to ED within 72 hours using data mining

Cut-off	Training set: 216,239 (return: 10,067)			Testing set: 120,113 (return: 5,452)		
	Overall	Sensitivity (return accuracy)	Specificity (no return accuracy)	Overall	Sensitivity (return accuracy)	Specificity (no return accuracy)
S1	94.9%	12.9%	98.9%	94.8%	7.7%	99.0%
S2	59.4%	59.9%	59.3%	57.8%	59.5%	57.7%

CONCLUSION

Patients with unscheduled ED return visits may reflect a care issue. While we noted that non-clinical factors such as social issues better predicted re-attendances than clinical factors, we were not able to establish a good prediction model with high sensitivity and specificity. The lack of good prediction rules to predict re-attendance could mean that ED had provided their best care possible based on the clinical judgement and had not missed out on significant clinical signs. We suspect that with more comprehensive coding of social issues, the predictive model could improve. We also did not find evidence to suggest that one particular prediction approach had outperformed significantly than the rest in this study.

GRAVITY MODEL FOR ESTIMATING ACUTE HOSPITAL CATCHMENT

Teow Kiok Liang, Dr Zhu Zhecheng, Phua Hwee Pin[1], Zhao Zheng[1], Dr Stefan Ma[1], Dr Kelvin Bryan Tan[2]
[1] Ministry of Health, Epidemiology and Disease Control Division
[2] Ministry of Health, Policy Research & Economics Office

BACKGROUND

Given the small geographical size of Singapore and freedom of choice, healthcare facilities often do not have a definite and well-defined catchment. This is particularly evident for tertiary care services where people are more willing to travel for their preferred choice of provider. The inpatient workload distribution across the hospitals shows that a substantial proportion of patients do not necessarily patronise the hospitals nearest to them (Table 1).

An accurate projection of regional level demand is therefore needed to inform planning of healthcare facilities and upgrading of existing ones, and for the regional health systems to plan their services. This study presented an approach to estimate the workload distribution across the acute care hospitals in Singapore, especially when new hospitals are built.

Table 1 – Inpatient workload distribution by hospitals for the top 10 planning areas in 2013

Planning Area	AH	CGH	KTPH	NUH	SGH	TTSH	Total
Bedok	0.0%	60.0%	2.0%	3.0%	24.0%	11.0%	100.0%
Bukit Merah	13.0%	3.0%	3.0%	9.0%	67.0%	5.0%	100.0%
Tampines	1.0%	66.0%	2.0%	3.0%	19.0%	10.0%	100.0%
Hougang	3.0%	11.0%	9.0%	3.0%	20.0%	54.0%	100.0%
Ang Mo Kio	2.0%	3.0%	16.0%	3.0%	13.0%	64.0%	100.0%
Jurong West	7.0%	2.0%	3.0%	63.0%	20.0%	5.0%	100.0%
Toa Payoh	2.0%	3.0%	2.0%	3.0%	12.0%	78.0%	100.0%
Woodlands	4.0%	3.0%	45.0%	12.0%	18.0%	19.0%	100.0%
Geylang	2.0%	23.0%	2.0%	3.0%	26.0%	43.0%	100.0%
Yishun	2.0%	3.0%	59.0%	5.0%	12.0%	20.0%	100.0%

AH – Alexandra Hospital; CGH – Changi General Hospital; KTPH – Khoo Teck Puat Hospital;
NUH – National University Hospital; SGH – Singapore General Hospital; TTSH – Tan Tock Seng Hospital

METHODS

We used the analogy of a "gravity model" to explain and predict the distribution of workload ("pull") across the hospitals. This model assumes patients' choices of hospitals are:

a) Inversely proportional to the square of distance
b) Proportional to the "mass" of the facilities. This "mass" factor is used to account for the fact that each facility has a different "pulling force".

These "mass" coefficients were empirically fitted with actual utilisations using optimisation technique. The fitting methodology is similar in principle to a regression model.

RESULTS

We fitted separately for emergency department (ED) attendances, day surgeries, inpatient surgeries and Specialist Outpatient Clinic (SOC) attendances in 2013. The fitted mass coefficients are presented in Table 2. In the model, we chose Hospital 3 as the "reference" hospital with coefficient "1". We see that the variation in mass coefficients, and therefore patients' preference for a particular hospital for ED is the smallest, and highest in SOC.

Table 2 - Fitted mass coefficients

Hospitals	ED	Day surgery	Inpatient surgery	SOC
H1	0.5	0.7	0.7	0.6
H2	1.0	1.2	0.7	0.7
[H3]	1.0	1.0	1.0	1.0
H4	0.9	2.1	1.2	1.9
H5	1.1	2.7	3.2	3.3
H6	1.6	4.0	4.8	5.7

[ ] Reference group

CONCLUSION

We developed a method to calibrate the "attractiveness" of hospitals using the analogy of gravity force. With new hospitals coming along, we can use this model, including the coefficients of the new hospitals, to estimate the new distribution across the hospitals.

PROJECTS

HEALTH & WELFARE ECONOMICS

A RETROSPECTIVE COHORT STUDY LOOKING AT MEDICAL COSTS INCURRED AT THE END-OF-LIFE FOR PATIENTS WHO DIED IN AN ACUTE CARE HOSPITAL

Dr Gary Ang Yee, Dr Heng Bee Hoon, Kelvin Teo Wee Sheng

BACKGROUND

A systematic review showed that there is an exponential increase in costs as death approaches with hospital services being the cost driver. Palliative services, which are relatively under utilised, are associated with lower expenditures than hospital-based care. Many studies suggest that medical expenditure is related to proximity to death but on the other hand, medical expenditure in the last year of life decreases with increasing age.

It has been found that 57.0% of elderly people in Singapore die in hospitals, and this proportion decreased with age. An economic impact analysis of an end-of-life programme for nursing home residents showed that there was cost savings of S$7,129 over the last 3 months of life and S$3,703 over the last month of life. As little else is known about the situation in Singapore, we have undertaken a study to look at the end-of-life direct medical costs of inpatient deaths in Singapore, the cost breakdown, and also explore factors associated with cost at 30 days, 60 days, 90 days and 360 days preceding death. The results will also serve as a basis for evaluation of future interventions on reducing end-of-life direct medical costs among inpatients.

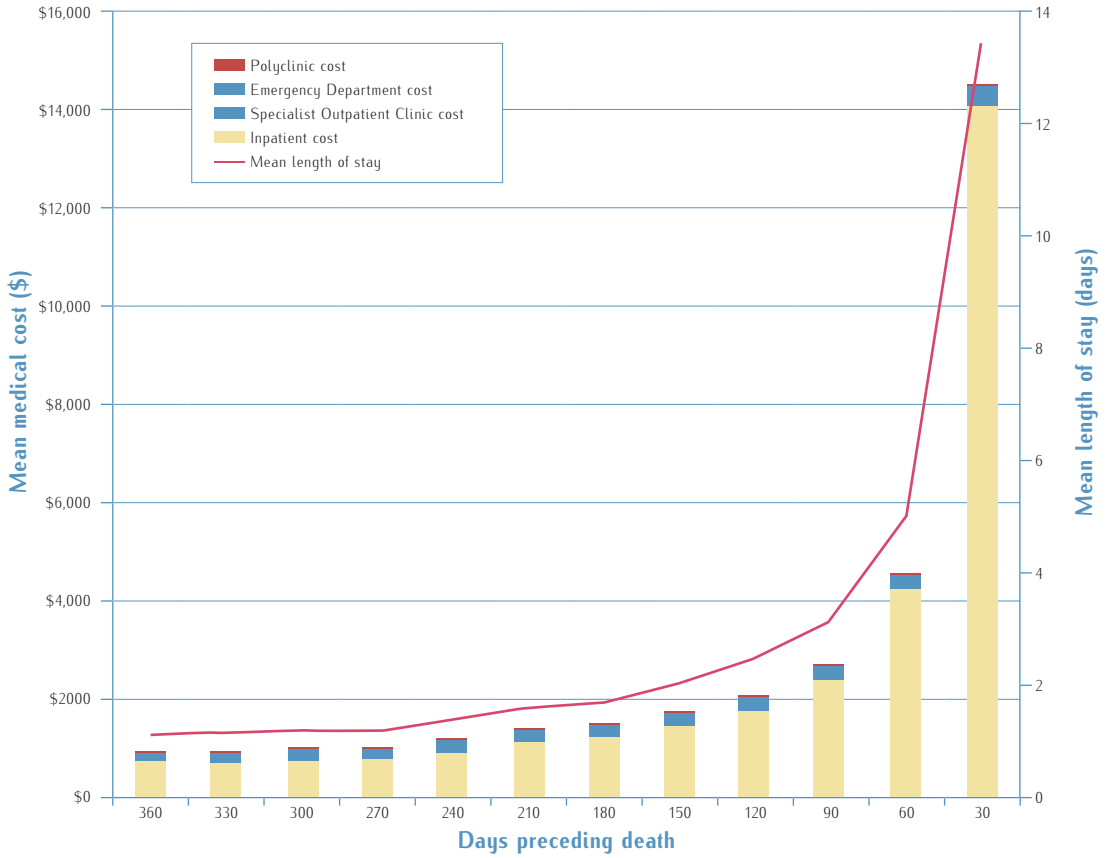
METHODS

This was a retrospective cohort study where healthcare utilisation in the 360 days preceding death was matched with demographics and causes of death. Patients who died in the emergency department or were brought in dead were excluded from the study. A generalised linear regression model was used to conduct the univariate analysis, followed by multivariate analysis.

RESULTS

There were a total of 2,162 inpatient deaths in an acute care hospital in Singapore in 2013. Majority of cost was incurred for admissions, followed by specialist outpatient clinic visits, emergency department visits and primary care clinic visits (Figure 1). 43.5% of costs were incurred in the last 30 days of life. Higher Charlson Comorbidity Index was associated with higher costs, while increasing age and use of palliative services were associated with lower costs.

Figure 1 – Mean medical cost and mean length of stay by days preceding death



CONCLUSION

We have looked at the direct end-of-life medical costs and the cost breakdown among patients who died in an acute care hospital in Singapore. We also identified variables that were associated with cost, and propose further studies to fill up the gap in this area.

MEASURING HEALTHCARE PRODUCTIVITY IN TAN TOCK SENG HOSPITAL

Dr Joseph Antonio D. Molina, Kelvin Teo Wee Sheng, Dr Heng Bee Hoon, Dr Eugene Fidelis Soh[1]
[1] Tan Tock Seng Hospital

BACKGROUND

The Singapore healthcare system is acknowledged as among the most efficient systems in the world, having achieved favourable health outcomes despite relatively low healthcare expenditure. Maintaining the current level of productivity and efficiency may however be increasingly more difficult with the ageing of the population and the associated increase in chronic diseases. While interventions are in place to address the changing demographics, there is a need to measure the healthcare system's ability to cope with these challenges. This was a baseline study to assess the level of productivity in Tan Tock Seng Hospital (TTSH) from 2011 to 2013 using selected ratio measures.

METHODS

The study started with a scoping exercise to identify suitable indicators and methods for measuring productivity in the healthcare setting. After conducting a literature search, a preliminary list of indicators was presented to the stakeholders for consideration. The importance of the indicator, the availability of the data and the manner by which the necessary data were to be extracted were among the factors considered. Data for fiscal years 2011, 2012 and 2013 were requested from the Finance, Office of Clinical Governance and Human Resource departments at TTSH. The data were used as the numerators and denominators for the individual productivity ratio measures. For cost indicators, dollar values for years 2012 and 2013 were deflated to 2011 values based on the Singapore consumer price index for medical treatment.

RESULTS

Salary and benefits have grown in tandem with revenue per employee. Employee salaries and benefits expense per admitted patient has increased over 3 years (Table 1).

Table 1 – Changes in inflation-adjusted productivity measures, 2011 to 2013

Productivity measure	Formula	2011	2012 deflated to 2011 $ (% change from previous year)	2013 deflated to 2011 $ (% change from previous year)
Recurrent cost per casemix adjusted separation[1]	N: Casemix adjusted number of separations D: Recurrent hospital cost	-	$5,897.44	$5865.24 (-0.55)
Revenue per employee	N: Net patient revenue D: Number of hospital staff	$41,292.81	$41,572.86 (+0.68)	$43,549.46 (+4.75)
Salary and benefits expense per full-time equivalent personnel	N: Salary expense + employee benefits expense D: Number of full time equivalent personnel	$66,465.74	$66,497.89 (+0.05)	$69,701.94
Salaries, wages & benefits per adjusted patient day	N: Salaries, wages & benefits ($) D: Adjusted patient day	$539.82	$545.48 (+1.05)	$566.24 (+3.81)

[1]Casemix index not computed for 2011 as different Diagnosis-related Group (DRG) systems were used in 2012 and 2013
N – numerator; D – denominator

Overhead cost has decreased over 3 years with a greater reduction in the last year. Revenues have increased for every dollar of assets over 3 years with slower growth in the last year (Table 2).

Table 2 – Changes in other selected productivity measures, 2011 to 2013

Productivity measure	Formula	2011	2012 (% change from previous year)	2013 (% change from previous year)
Full-time equivalent personnel per 100 adjusted discharges)	N: Number of full-time equivalent personnel x100 D: Adjusted discharges	5.52	6.04 (+9.42)	5.66 (-5.29)
Salary and benefits expense, as a % of operating expense	N: (Salary expense + employee benefits expense) x100 D: Operating expense, total	53.92	54.43 (+0.95)	55.01 (+1.07)
Overhead[2] expense as a % of operating expense	N: Overhead expense, x100 D: Operating expense, total	13.09	13.06 (-0.27)	12.39 (-5.06)
Asset turnover ratio[3]	N: Net patient revenue D: Assets	0.54	0.61 (+12.3)	0.63 (+4.21)

[2]E.g. of overheads=general expenses, administration and registration, utilities, maintenance, insurance, and personnel costs of non-patient services, e.g. management and administration
[3]Reflects ability of the institutor to utilise assets to generate revenue
N – numerator; D – denominator

CONCLUSION

The findings should be viewed against a backdrop of hospital quality indicators. While research as well as education and training activities should be included among the outputs, these were not reflected in the results due to the lack of data.

PROJECTS

RESEARCH DESIGN & METHODOLOGIES

TIME DEPENDENT MARKOV PROCESS — THE PATIENT FLOW MODEL BEHIND THE REGRESSION TO THE MEAN EFFECT IN HOSPITAL INPATIENT DATA

Alex You Xiaobin, Palvannan R.K., Dr Heng Bee Hoon

BACKGROUND

We often observe health services utilisation (eg. hospital admissions) of patients to be high in one year, low in the next and high again the following year ("yo-yo" effect), even without intervention. In statistics, this natural process is summarised as the regression to the mean (RTM) effect. Arising from the observation of the RTM effect in hospital inpatient data, a series of yearly transition matrices were derived to depict the patient flow pattern in different risk categories. Through studying the Markov transition probability, we can better understand the RTM effect. The inherent Markovian property is a refined summary and a more accurate estimation of the RTM effect.

METHODS

A cohort of patients who had hospital admissions in 2008 were studied. Their yearly inpatient utilisation data were followed until 2013. All patients were divided into different risk categories of "No admission", "1-2 admissions", "3-4 admissions" and "5+ admissions" according to their yearly admission in 2009 to 2013 aggregation. A Markov Chain with absorbing state "death" was built and estimated using the bootstrap method. A time-dependent Markov model was built to show the mild change of transition patterns over time. The Markov model was later used in utilisation projection.

RESULTS

The 3-yearly transition matrices with bootstrap standard deviation are shown in Table 1. The time-dependent Markov model was fitted with linear regression, with the results shown in Table 2. The Markov model can be applied to estimate the RTM effect for each risk category. Taking the risk categories and the group mean admission of all patients in 2010 as known information, we applied the Markov transition matrix to project the group mean in 2010. The true and predicted group mean were very close (Table 3).

Table 1 – Transition matrix of 2008 cohort through 2012

	Admission rate in 2010 (Standard deviation estimate*)				
Admissions in 2009	0	1-2	3-4	5+	Died
0	88.6 (0.5)	8.8 (0.4)	0.7 (0.1)	0.2 (0.1)	1.7 (0.2)
1-2	60.6 (1.7)	25.5 (1.4)	5.3 (0.8)	2.1 (0.5)	6.6 (0.8)
3-4	29.7 (3.9)	31.0 (3.9)	12.3 (2.7)	11.4 (2.6)	15.6 (3.0)
5+	15.7 (4.2)	21.2 (4.9)	18.3 (4.8)	24.5 (5.2)	20.3 (4.7)
	Admissions in 2011				
Admissions in 2010	0	1-2	3-4	5+	Died
0	90.1 (0.4)	7.5 (0.4)	0.6 (0.1)	0.2 (0.1)	1.6 (0.2)
1-2	60.7 (1.9)	25.1 (1.6)	5.2 (0.8)	1.7 (0.5)	7.3 (1.0)
3-4	28.5 (4.0)	28.9 (4.2)	14.6 (3.3)	11.4 (3.1)	16.5 (3.5)
5+	14.8 (4.7)	22.3 (5.1)	16.3 (4.7)	27.4 (5.6)	19.1 (5.0)
	Admissions in 2012				
Admissions in 2011	0	1-2	3-4	5+	Died
0	90.5 (0.4)	7.1 (0.4)	0.7 (0.1)	0.1 (0.1)	1.6 (0.2)
1-2	58.4 (2.0)	26.0 (1.8)	6.1 (1.0)	2.2 (0.6)	7.4 (1.1)
3-4	26.5 (4.5)	32.7 (4.9)	15.7 (3.8)	10.2 (3.2)	15.0 (3.9)
5+	11.4 (4.4)	19.1 (5.2)	17.2 (5.3)	29.3 (6.1)	23.0 (5.9)

*Using bootstrap method

Table 2 – Time-dependent Markov Model

(a)	0	1-2	3-4	5+	Died
0	88.8	8.6	0.7	0.2	1.7
1-2	61.0	25.3	5.1	2.0	6.7
3-4	29.8	30.0	12.6	11.6	16.0
5+	16.1	21.9	17.8	24.7	19.5

(a) Intercept matrix

(b)	0	1-2	3-4	5+	Died
0	1.0	-0.8	-0.0	-0.1	-0.1
1-2	-1.1	0.2	0.4	0.0	0.4
3-4	-1.6	0.9	1.7	-0.6	-0.3
5+	-2.1	-1.0	-0.6	2.4	1.3

(b) Slope matrix

Table 3 – Utilisation projection

2010 Groups	Weight	2010 Mean	2011 Mean	Markov Model
0	77.8%	0.00	0.15	0.18
1-2	14.3%	1.25	0.71	0.74
3-4	2.5%	3.36	1.76	1.89
5+	1.3%	7.21	3.48	2.97
Died	4.1%	1.60	0.00	0.00
Weighted Sum of Error				0.019

CONCLUSION

Through the cohort study on hospital inpatient data, we found a strong RTM effect from year to year. The natural RTM effect should be isolated in pre-post test experimental design and intervention evaluation. To evaluate the outcome of health intervention, a control group is necessary. If a control group is unavailable, the cautious inference from historical data is a sub-optimal choice.

In this study, the RTM effect was explained and estimated by the Markov model. The RTM effect of a certain cohort appears as the transition among its subgroups. Through building a Markov model, we can quantify the transition and project the utilisation. The 3-yearly transition matrices and the time-dependent Markov model both conclude the mild ageing and growing trend utilisation over time.

ONLINE E-LEARNING FOR UNDERGRADUATES IN HEALTH PROFESSIONS: A SYSTEMATIC REVIEW OF THE IMPACT ON KNOWLEDGE, SKILLS, ATTITUDES AND SATISFACTION

Dr Pradeep Paul George, Nikos Papachristou[1], José Marcano Belisario[1], Wang Wei[2], Petra A Wark[1], Ziva Cotic[1], Kristine Rasmusen[1], René Sluiter[3], Eva Riboli-Sasco[1], Lorainne Tudor Car[1], Eve Marie Musulanov[1], Dr Joseph Antonio D. Molina, Dr Heng Bee Hoon, Zhang Yanfeng[2], Erica Lynette Wheeler[4], Najeeb Al Shorabji[1], Azeem Majeed[1], Prof Josip Car[1,5]

[1] Imperial College, Department of Primary Care and Public Health, London
[2] Capital Institute of Paediatrics, Department of Integrated Early Childhood Development, China
[3] Radboud University Nijmegen, Department of Health Evidence, The Netherlands
[4] World Health Organisation, Knowledge, Ethics and Research, Switzerland
[5] Lee Kong Chian School of Medicine, Health Services and Outcomes Research Programme

BACKGROUND

Health systems worldwide are facing shortages in the health professional workforce. Several studies have demonstrated the direct correlation between the availability of health workers, coverage of health services, and population health outcomes. To address this shortage, online e-Learning is increasingly being adopted in health professionals' education. To inform policy making in online e-Learning, we need to determine its effectiveness.

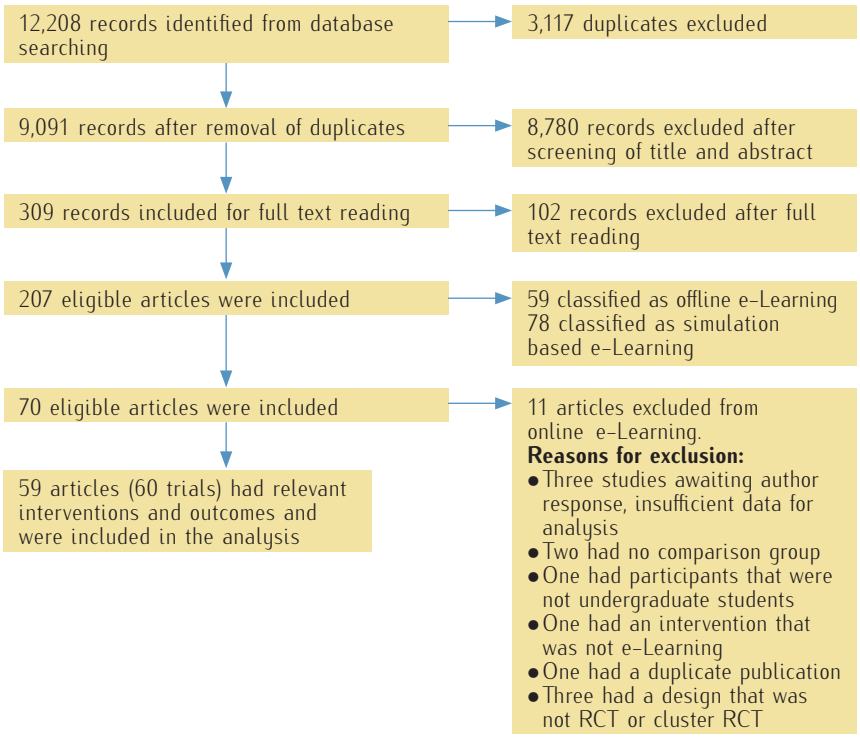
METHODS

We performed a systematic review of the effectiveness of online e-Learning through a comprehensive search of the major databases for randomised controlled trials (RCT) that compared online e-Learning to traditional learning or alternative learning methods. The search period was from January 2000 to August 2013. We included articles which primarily focused on students' knowledge, skills, satisfaction and attitudes toward e-Learning and cost-effectiveness and adverse effects as secondary outcomes. Two reviewers independently extracted data from the included studies. Due to significant heterogeneity among the included studies, we presented our results as a narrative synthesis.

RESULTS

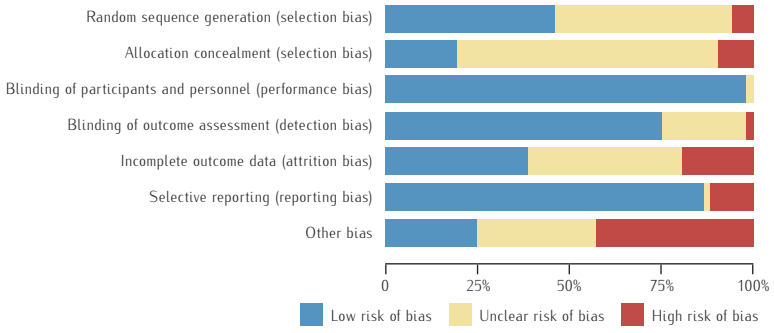
Fifty–nine studies, including 6,750 students enrolled in medicine, dentistry, nursing, physical therapy and pharmacy studies, met the inclusion criteria (Figure 1). Twelve of the 50 studies testing knowledge gains found significantly higher gains in the online e-Learning intervention groups compared to traditional learning, whereas 27 studies did not detect significant differences or found mixed results. Eleven studies did not test for differences.

Figure 1 – Flowchart of studies included in the review



Six studies detected significantly higher skill gains in the online e-Learning intervention groups, whilst three other studies testing skill gains did not detect differences between groups and one study showed mixed results. Twelve studies tested students' attitudes, of which eight studies showed no differences in attitudes or preferences for online e-Learning. Students' satisfaction was measured in 29 studies, four studies showed higher satisfaction for online e-Learning and 20 studies showed no difference in satisfaction between online e-Learning and traditional learning. Risk of bias was high for several of the included studies (Figure 2).

Figure 2 – Overall risk of bias



CONCLUSION

The current evidence base suggested that online e-Learning is equivalent, possibly superior to traditional learning. These findings present a potential incentive for policy makers to cautiously encourage its adoption, while respecting the heterogeneity among the studies.

APPLICATION OF SPARSE MATRIX CLUSTERING WITH CONVEX-ADJUSTED DISSIMILARITY MATRIX IN AN AMBULATORY HOSPITAL SPECIALIST SERVICE

Alex You Xiaobin, Dr Heng Bee Hoon, Teow Kiok Liang

BACKGROUND

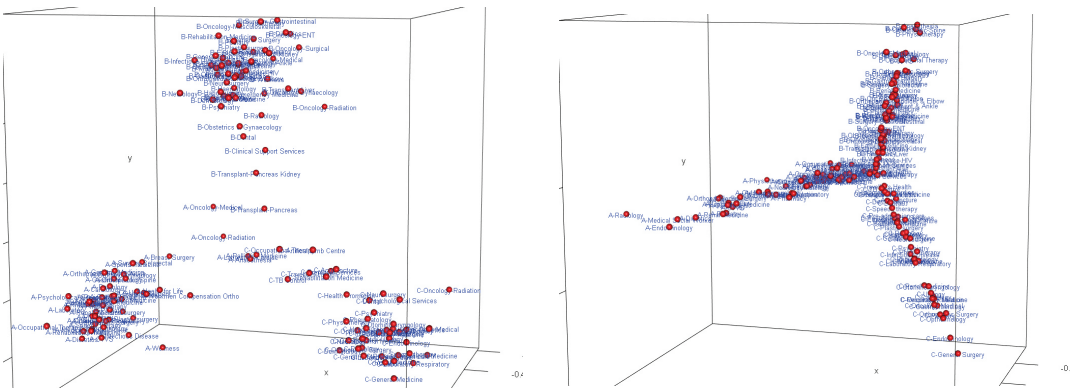
Patients with chronic diseases and complications may frequently visit different specialists. Analytics could help deliver patient-centric seamless care by providing insights on the visit patterns of this group of patients, so that utilisation of healthcare resources can be optimised. A new perspective focusing on patients' specialist utilisation records combined with statistical learning methodology can quantify the tightness of links between different specialties and highlight important specialist clusters.

METHODS

Cosine angular dissimilarity matrix was used to measure connections among 163 specialties in three Singapore general hospitals based on 931,504 specialist attendance visits in 2013. A convex transformation on angular dissimilarity was introduced to solve low similarity problem caused by matrix sparsity, and thus improve hierarchical clustering performance. The objective was to improve transformation by maximising variance of off-diagonal dissimilarity coefficients.

Ward's method was used in clustering with dissimilarity matrix. The visualisations of the distance matrices before and after convex transformation are shown in Figure 1. Interactive visualisation of sortable matrix was used to highlight important specialist clusters.

Figure 1 – Visualisation of distance matrix



Before transformation

After transformation

RESULTS

Through clustering, 20 significant clusters were identified (Table 1). Common clusters such as orthopaedics, oncology-surgery, internal medicine, neuroscience, were found among the three hospitals. Components of common clusters among hospitals were similar.

Table 1 – Clustering result

Hospital A	Hospital B	Hospital C
Orthopaedic Cluster	**Orthopaedic Cluster**	**Orthopaedic Cluster**
Orthopaedic Surgery	Orthopaedic Surgery	Orthopaedic Surgery
Physiotherapy	Orthopaedic-Spine	Hand Surgery
Occupational Therapy	Hand Surgery	Physiotherapy
Sports Medicine	Anaesthesia	Artificial Limb Centre
Medical Records Office	Orthopaedic-Shoulder & Elbow	Emergency Medicine
Orthopaedic-Spine	Occupational Therapy	**Internal Medicine Cluster**
Orthopaedic-Sports	Physiotherapy	Cardiology
Workmen Compensation Orthopaedic	Sports Medicine	Urology
Internal Medicine Cluster	**Internal Medicine Cluster**	**Gastroenterology Cluster**
Dietetics	Cardiology	Endocrinology
Endocrinology	Gastroenterology	Renal Medicine
Renal Medicine	Endocrinology	General Medicine
Medical Social Worker	Rheumatology	Podiatry
Podiatry	Ophthalmology	Haematology
Oncology-Surgery Cluster	Respiratory Medicine	**RAI-Eye-ENT Sub-Cluster**
Breast Surgery	**Oncology-Surgery Cluster**	Ophthalmology
Oncology-Medical	Oncology-Medical	RAI
Oncology-Radiation	Oncology-Radiation	Otorhinolaryngology
Neuroscience Cluster	Breast Surgery	**Oncology-Surgery Cluster**
Psychiatry	Oncology-Gynaecology	General Surgery
Neurology	Oncology-Surgical	Oncology-Medical
Psychological Services	**Neuroscience Cluster**	Oncology-Radiation
Speech Therapy	Neurology	Palliative Medicine
Neurosurgery	Neurosurgery	**Neuroscience Cluster**
Laboratory	Rehabilitation Medicine	Neurology
Rehabilitation Medicine	**O&G Cluster**	Rehabilitation Medicine
Anaesthesia	Obstetrics & Gynaecology	Acupuncture
Respiratory Cluster	Psychiatry	Psychiatry
Respiratory Medicine	**Speech-Dietetic Cluster**	Neurosurgery
Laboratory-Respiratory	Speech Therapy	Psychological Services
Eye-ENT Cluster	Dietetics	**Speech-Dietetic Cluster**
Ophthalmology	**Transplant Cluster**	Speech Therapy
Otorhinolaryngology	Renal Medicine	Dietetics
Pain	Transplant-Kidney	**Respiratory Cluster**
	Transplant-Liver	Respiratory Medicine
	Transplant-Pancreas	Laboratory-Respiratory

ENT – Ear, Nose & Throat; O&G – Obstetrics & Gynaecology; RAI – Rheumatology, Allergy & Immunology

CONCLUSION

Patient utilisation records can bring new and systematic insights of cooperative specialist services alongside traditional clinical research. Convex adjustment improved performance of Ward's method on low similarity distance matrix significantly. Hierarchical clustering on convex-adjusted dissimilarity matrix was effective in discovering specialist clusters.

WORRY ABOUT CAREGIVING PERFORMANCE: A CONFIRMATORY ANALYSIS

Li Ruijie, Dr Chong Mei Sian[1,2], Dr Mark Chan Peng Chew[1,2], Dr Laura Tay Bee Gek[1,2], Dr Noorhazlina Binte Ali[1,2], Tengku Mohd K. Shariffah Mahanum[2], Dr Lim Wee Shiong[1,2]

[1] Tan Tock Seng Hospital, Department of Geriatric Medicine

[2] Tan Tock Seng Hospital, Institute of Geriatrics and Active Ageing

BACKGROUND

Caregiver burden of people with dementia (PwD) has been studied extensively in recent years. The Zarit Burden Interview (ZBI) is a 22-item instrument commonly used to measure caregiving burden in caregivers of PwD. Initially conceptualised as a uni-dimensional model, subsequent work have found that the ZBI consist of at least two factors – role and personal strain. Role strain refers to stress due to role conflict and overload while personal strain refers to how the experience is personally stressful.

Further research uncovered another factor – worry about caregiving performance (WaP). WaP consists of items 20 and 21 of the ZBI ("Do you feel you should be doing more for your relative?" and "Do you feel you could do a better job in caring for your relative?" respectively), and is of particular interest and importance as it appears to lie on a continuum. On the milder end of WaP, it can be a motivating factor to improve on the caregiving task but can be potentially stressful if it progresses to guilt on the more severe end.

In this study, we aimed to: 1) determine if there was evidence to support the factor WaP; 2) determine if separating role strain into two factors was better than keeping it as one factor; and 3) explore in depth the relationship of WaP with various patient and caregiver characteristics.

METHODS

A cross-sectional prospective design was adopted. 466 patient-caregiver dyads were recruited from the Memory Clinic at Tan Tock Seng Hospital (TTSH) from January 2010 to December 2011. Confirmatory factor analysis was used to compare the following factor models: 1) uni-dimensional model (all items); 2) two-factor model comprising role strain and personal strain; 3) three-factor model, comprising a single role strain factor, a personal strain factor and WaP; 4) four-factor model, namely role strain due to demands of care, role strain secondary to loss of control over the situation, personal strain and WaP; and 5) four-factor model comprising captivity, loss of control, personal strain, and self-criticism.

To fulfil Objective 1, we compared the models with and without WaP to determine which models had a better fit with the data. For Objective 2, we compared Models (1) and (3) to see which had the superior model fit, and for Objective 3, linear regressions were conducted for the best fitting model to determine the relationships between the factors with the characteristics of the patient-caregiver dyad.

RESULTS

Table 1 and Table 2 summarises the results of the confirmatory factor analysis and regressions respectively. The confirmatory factor analyses showed that the models with WaP had better fit indices despite being more complex than the models without WaP. Also, the model that splits role strain into two factors was superior than the one that retained role strain as a single factor.

Table 1 – Confirmatory factor analysis fit indices

	df	χ^2	RMSEA	SRMR	NNFI	CFI
1 factor	209	1849.888	0.130	0.080	0.863	0.876
2 factor	134	1543.840 ***	0.150	0.087	0.844	0.864
3 factor (with WaP)	206	1018.985 ***	0.092	0.065	0.931	0.939
4 factor (with WaP)	203	969.183 ***	0.090	0.063	0.934	0.942
4 factor (with WaP)	129	689.290 ***	0.097	0.061	0.938	0.948

*p<.05; **p<.01; ***p<.001
df – degrees of freedom; χ^2 – Chi-square; RMSEA – Root Mean Square Error of Approximation;
SRMR – Standardised Root Mean Square Residual; NNFI – Non-normed Fit Index; CFI – Comparative Fit Index

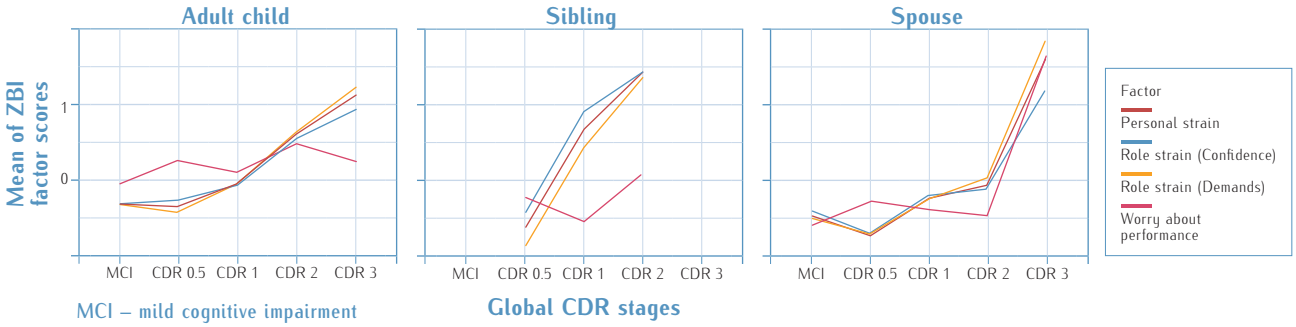
Table 2 – Regression of factors and ZBI total score on caregiver and care-recipient characteristics

	Total ZBI			Role strain (Demands)			Role strain (Control)			Personal strain			Worry about performance		
Regression	b	β	p-value	b	β	p-value	b	β	p-value	b	β	p-value	b	β	p-value
Relationship with care-recipient [Reference: Spouse]															
Adult child	.207	.126	.023*	.245	.123	.029*	.316	.161	.005**	.284	.142	.012*	.329	.184	.003**
Sibling	.509	.092	.048*	.506	.075	.112	.693	.104	.029*	.631	.093	.049*	-.062	-.010	.845
Others	.085	.016	.726	.086	.014	.772	.032	.005	.915	.053	.008	.860	.172	.030	.562
Caregiver gender [Reference: Female]															
Male	-.007	-.004	.918	-.032	-.016	.716	.002	.001	.986	-.014	-.007	.874	-.081	-.045	.359
Living with care-recipient [Reference: No]															
Yes	.022	.012	.796	.039	.017	.714	.025	.011	.812	.025	.011	.813	-.151	-.071	.158
Caregiver education	-.010	-.061	.244	-.008	-.039	.457	-.016	-.080	.134	-.012	-.060	.258	-.002	-.011	.853
BADL (0-100)	-.001	-.026	.581	-.001	-.023	.638	.000	-.013	.792	.000	-.013	.794	.001	.057	.288
IADL (0-23)	-.017	-.129	.031*	-.028	-.175	.004**	-.025	-.156	.011*	-.025	-.159	.009**	.003	.021	.756
NPI-Q severity (0-36)	.011	.071	.407	.007	.040	.647	.014	.077	.375	.010	.055	.522	.032	.189	.049*
NPI-Q distress (0-60)	.035	.336	.000***	.042	.323	.000***	.037	.289	.001***	.041	.321	.000***	.001	.009	.924
CMMSE (0-28)	.004	.030	.635	.006	.037	.565	.005	.034	.606	.006	.037	.567	-.002	-.011	.875
Adjusted R^2	.285		.000***	.262		.000***	.248		.000***	.260		.000***	.091		.000***

*p<.05; **p<.01; ***p<.001, N= 403.
b – Unstandardised coefficient; β – Standardised coefficient;
BADL – Basic Activities of Daily Living; IADL – Instrumental Activities of Daily Living;
NPI-Q – Neuropsychiatric Inventory Questionnaire; CMMSE – Chinese Mini Mental Status Examination

The regression analyses showed that WaP has different predictors compared to other factors, providing evidence of its unique nature. We further explored the relationship between the different factors of ZBI in relation to the Clinical Dementia Rating (CDR) stages, stratified by patient-caregiver dyad relationship (Figure 1). The results suggested that there were unique differences in the changes of burden across CDR stages in the different patient-caregiver dyad relationship. These results should be interpreted with caution as they were not statistically significant. Future studies can focus on validating these results.

Figure 1 – Caregiving burden profiles of caregiver with different relationships with care recipient



CONCLUSION

We provided evidence that WaP was a unique factor within the ZBI given its superior fit indices in confirmatory factor analyses and patterns of predictors in the linear regressions. We also provided evidence to support splitting role strain into two factors. Finally, we highlighted the differences in burden experienced by the different patient-caregiver dyad relationships across CDR stages. The results provide additional insight into the phenomenon of caregiving burden.

PUBLICATIONS

Original Articles

1. *Ang J,* ***Meng F****, Sun J.* Two-stage stochastic linear programmes with incomplete information on uncertainty. European Journal of Operational Research 2014; 233 (1): 16-22.

2. ***Zhu ZC****.* An online short-term bed occupancy rate prediction procedure based on discrete event simulation. Journal of Hospital Administration 2014; 3 (4): 37-42.

3. ***George PP****,* ***Heng BH****, Wong LY,* ***Ng CWL****.* Determinants of health-related quality of life among community dwelling elderly. Annals Academy of Medicine Singapore 2014; 43 (1): 3-10.

4. ***Teo WSK****, Govinda Raj A,* ***Tan WS****,* ***Ng CWL****,* ***Heng BH****, Leong IYO.* Economic impact analysis of an end-of-life programme for nursing home residents. Palliative Medicine 2014; 28 (5): 430-437.

5. *Lim LHY, Xiang L, Wong NLY, Yuen KCP,* ***Li R****.* Validation of the Paediatric Hearing Impairment Caregiver Experience (PHICE) Questionnaire. Annals Academy of Medicine Singapore 2014; 43 (7): 362-370.

6. *Tan KB,* ***Tan WS****, Bilger M, Ho CWL.* Monitoring and evaluating progress towards universal health coverage in Singapore. PLOS Medicine 2014; 11 (9): e1001695 / doi:10.1371/journal.pmed.1001695.s001.

7. ***Tan WS****,* ***Ding YY****, Xia WC,* ***Heng BH****.* Effects of a population-based diabetes management programme in Singapore. The American Journal of Managed Care 2014; 20 (9): e388-e398.

8. ***Ng CWL****, Luo N,* ***Heng BH****.* Health status profiles in community-dwelling elderly using self-reported health indicators: A latent class analysis. Quality of Life Research 2014; 23 (10): 2889-2898.

9. ***Ng CWL****,* ***Tan WS****,* ***George PP****, Wong LY,* ***Heng BH****.* Association of socioeconomic status and social support with depressive symptoms among the elderly in Singapore. Annals Academy of Medicine Singapore 2014; 43 (12): 576-587.

10. ***Molina JAD****, Seow H,* ***Heng BH****,* ***Chong WF****, Ho B.* Outcomes of direct and indirect Medical Intensive Care Unit admissions from the emergency department of an acute care hospital. BMJ Open 2014; 4 (11): e005553.

Systematic Reviews & Review Articles

11. ***George PP***, ***Molina JAD***, ***Heng BH***. The methodological quality of systematic reviews comparing intravitreal bevacizumab and alternates for neovascular age related macular degeneration: A systematic review of reviews. Indian Journal of Ophthalmology 2014; 62 (7): 761-767.

12. *Rasmussen K, Belisario JM, Wark PA,* ***Molina JA****, Loong SL, Cotic Z, Papachristou N, Riboli-Sasco E, Car LT, Musulanov EM, Kunz H, Zhang Y,* ***George PP****,* ***Heng BH****, Wheeler EL, Shorbaji NA, Svab I, Atun R, Majeed A, Car J.* Offline e-Learning for undergraduates in health professions: A systematic review of the impact on knowledge, skills, attitudes and satisfaction. Journal of Global Health 2014; 4 (1): 010405.

13. ***George PP****, Papachristou N, Belisario JM, Wang W, Wark PA, Cotic Z, Rasmussen K, Sluiter R, Riboli-Sasco E, Car LT, Musulanov EM,* ***Molina JA****,* ***Heng BH****, Zhang Y, Wheeler EL, Shorbaji NA, Majeed A, Car J.* Online e-learning for undergraduates in health professions: A systematic review of the impact on knowledge, skills, attitudes and satisfaction. Journal of Global Health 2014; 4 (1): 010406.

Letter

14. *Wee SL, Li Y,* ***Sun Y****, Chua YX.* Determinants of long-term care needs of community-dwelling older people in Singapore. Journal of the American Geriatrics Society 2014; 62 (12): 2453-2454.

Book Chapter

15. ***Zhu ZC***, ***Heng BH***, ***Teow KL***. Interactive data visualisation techniques applied to healthcare decision making [Chapter 3]. In Wang B, Li R, Perrizo W, editors. Big Data Analytics in Bioinformatics and Healthcare: IGI Global; 2014.

AWARDS & GRANTS

Conference Presentation Awards

Singapore Health & Biomedical Congress 2014, Singapore
September 2014

Singapore Young Investigator Award – Gold (Health Services Research)
Tan Woan Shin
An evaluation of the Dover Park Hospice Integrated Home Hospice Care pilot

Singapore Young Investigator Award – Silver (Health Services Research)
Li Ruijie
Worry about caregiving performance: A confirmatory analysis

Research Grants

NHG Small Innovative Grant

Development of a cloud-based patient health information system to assist population health management in National Healthcare Group
Dr Sun Yan (*PI*)
Pradeep Paul G Gunapal (*Co-investigator*)
Dr Heng Bee Hoon (*Co-investigator*)
Dr Tan Kok Leong, TTSH (*Co-investigator*)
Amount: $100,000

NTU-NHG Ageing Research Grant

Affordable U-healthcare platform for diabetes management
Dr Heng Bee Hoon (*NHG Lead PI*)
A/Prof Cho Nam-Joon, NTU (*NTU Lead PI*)
Amount: $248,000

TRAINING & EDUCATION

Data Analytics in Health Services Research – Causal effect and predictive models

January and October 2014
Speakers: ***Dr Sun Yan***
A/Prof Ding Yew Yoong

Health Services Research is an emerging discipline that deals with all aspects of understanding and promoting the effective organisation, analysis, management, and use of health care information to improve decision making. This half-day workshop introduced participants with programme evaluation through causal effect regression models and predictive modelling using big data.

Introduction to Qualitative & Mixed-Methods Research

February 2014
Speakers: *Dr Ooi Chee Kheong*
Mr Issac Lim
Mr Li Ruijie

Well-known for the abilities to discover novel insights, elucidate complicated processes, and strengthen research designs, qualitative research is an important component of any clinical and health services research programme. This interactive and hands-on workshop was designed to introduce participants to the philosophical as well as nuts-and-bolts matters of qualitative research. Participants explored pertinent issues related to qualitative research, including (but not limited to) whether qualitative research is antithetical to quantitative approaches; if qualitative research could be used in combination with other research approaches, including randomised controlled trials; different methods in qualitative research; and appraising the quality/rigor of qualitative research.

Introduction to Health Services Research

July 2014
Speakers: *Dr Joseph D. Molina*
Dr Pradeep Paul George
Ms Tan Woan Shin
Mr Teow Kiok Liang

This one-day course provided an overview of the basic concepts, rationale, general and discipline-specific methods used in carrying out health services research. The main objective was to familiarise participants with a repertoire of methods that were often encountered in the conduct of health services research. Essentially an introductory course, this served as a preparatory module for those interested in attending more in-depth courses on specific health services research topics.

Combining Quantitative and Qualitative Methods for Health Services Research

October 2014
Speaker: *Dr Fiona McMaster*

This one-day course aimed to provide participants with a better understanding of how quantitative and qualitative methods could be combined in health services research; reviewed how surveys and less structured interviews could be combined; considered the design of focus groups for data quality; and applied principles of mixed methods in data analysis and presentation.

CONFERENCE PRESENTATIONS

JANUARY — SMDM Asia-Pacific Conference, Singapore

1. **Zhu ZC, Teow KL**
   Comparison of system dynamics and discrete event simulation in application of specialist outpatient clinic modelling

2. Lim HY, Yang E, Wang HH, Hing WC, Chiam A, **Zhu ZC, Teow KL**
   Optimising repack sizes for outpatient pharmacy automated dispensing systems

3. **Meng FW, Palvannan RK, Teow KL**, Lam EGL, Ooi CK
   Understanding patient flows and consultation patterns for care delivery in emergency department

4. **Sun Y, Palvannan K, Teo KWS, Heng BH**, Ang B
   Cost-effective screening for MRSA colonisation upon hosptial admission by decision modelling

MAY — ISPOR 19th Annual International Meeting, Montreal

5. **Sun Y, George PP**, Tan N, Rajagopalan R, Lew YJ, **Heng BH**
   A risk stratification tool for screening for diabetic retinopathy among Type 2 diabetic patients

JUNE — 16th International Congress of the World Federation of Occupational Therapists, Yokohama

6. **Li R**, Ng LC, Noor Hafizah
   Refactoring of the SAFER-HOME to represent the occupational context of a person

JULY — 2nd International Conference on Big Data and Analytics in Healthcare, Singapore

7. **Meng FW, Palvannan RK, Teow KL**, Tay SY, Lam EGL, Ooi CK, Soh CKK
   Understanding complex patient flow pathways in emergency department using large scale data

CONFERENCE PRESENTATIONS

AUGUST — **9th Singapore Public Health & Occupational Medicine Conference, Singapore**

8. **Ang YG, Heng BH**
   Angiotensin-converting enzyme inhibitor, angiotensin receptor blocker, combination therapy and mortality in chronic kidney disease

9. **Teo KWS**, Loy FL, **Tan WS, Ang YG**, Tjan SY
   Economic burden of back pain

10. **Molina JAD**, Ismail NH, **Heng BH**, Leong IYO
    Engaging the community - An evaluation of a community-based falls prevention programme for the elderly

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SEPTEMBER — **Singapore Health & Biomedical Congress 2014, Singapore**

11. **Meng FW**, Tay SY, Ooi CK, Soh CKK, **Teow KL, Palvannan RK**
    Diagnosis and resource utilisation in emergency department: A descriptive and quantitative study

12. **Li R**, Chong MS, Chan PCM, Tay BGL, Ali N, Mahanum TMKS, Lim WS
    Worry about caregiving performance: A confirmatory analysis

13. Lee A, **Tan WS**, Yang SY, Chan S, Wu HY, Koh M
    Integrated Home Hospice Care – Impact on family caregiver satisfaction

14. Chemat J, Loy FL, Yang SY, **Teo WS**, Tjan SY
    Assessment of newly referred patients with low back pain: A nurse clinician's triage experience

15. **Meng FW**, Tay SY, Ooi CK, Soh CKK, **Teow KL, Palvannan RK**
    Diagnosis and resource utilisation in emergency department: A descriptive and quantitative study

16. **You XB, George PP, Palvannan RK, Heng BH**
    Validation and re-estimation of disease weights in Charlson Comorbidity Index among Singapore patients

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OCTOBER — **ILTC Quality Festival 2014, Singapore**

17. **Tan WS**, Lee A, Yang SY, Chan S, Wu HY, Koh M
    Integrated Home Hospice Care – Impact on family caregiver satisfaction

NHG Quality Day 2014, Singapore

18. Tan C, **Teow KL**
    The key to continued community healthcare: Actualising first appointments

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DECEMBER — **IEEE Symposium on Computational Intelligence in Big Data, Orlando**

19. **You XB, Teow KL, Heng BH**
    Application of Sparse Matrix Clustering with Convex-Adjusted Dissimilarity Matrix in an ambulatory hospital specialist service

THE TEAM

1. **Dr Heng Bee Hoon**
MBBS, MSc (Public Health), FAMS
Director

2. **A/Prof Ding Yew Yoong**
MBBS, FRCP, FAMS, MPH
Visiting Consultant
(Senior Consultant & Clinical Associate Professor, Geriatric Medicine, TTSH)

3. **Charis Ng Wei Ling**
BA (Psychology & Communications), MPH
Senior Research Analyst

4. **Cheryl Lobo**
BA (History)
Information Specialist

5. **Chong Wai Fung**
BN, MBA, MPH
Principal Research Analyst

6. **Dr Gary Ang Yee**
MBBS, MPH
Associate Consultant (Public Health)

7. **Ge Lixia**
BMed (Nursing), MSc (Physiology)
Research Analyst

8. **Dr Joseph Antonio D. Molina**
MD, MSc (Public Health)
Principal Research Analyst

9. **Kelvin Teo Wee Sheng**
BA (Economics) (Magna Cum Laude), MA (Economics)
Research Analyst

10. **Kenneth Lim Teck Kiat**
BCom (Hons Class 1)
Research Analyst

11. **Li Ruijie**
MSc (Occupational Therapy)
Senior Research Analyst

12. **Dr Meng Fanwen**
MSc (Operations Research), PhD (Operations Research)
Operations Research Specialist

13. **Dr Nakul Saxena**
BPharm, PhD (Epidemiology)
Research Analyst

14. **Palvannan R.K.**
BEng (Mechanical Engineering), MEng (Industrial & Systems Engineering)
Operations Research Specialist

15. **Dr Pradeep Paul George Gunapal**
BSMS, MSc (Epidemiology)
Principal Research Analyst

16. **Dr Sun Yan**
MSc (Data Mining), PhD (Medical Informatics)
Medical Informatics and Biostatistics Specialist

17. **Tan Woan Shin**
BSocSc (Hons) (Economics), MSocSc (Economics)
Principal Research Analyst

18. **Teow Kiok Liang**
BEng (Electrical Engineering), MSc (Industrial & Systems Engineering)
Operations Research Specialist

19. **Dr Zhu Zhecheng**
MSc (Information Engineering), PhD (Industrial & Systems Engineering)
Operations Research Specialist

20. **Alex You Xiaobin**
BEcon (Statistics), MSc (Statistics)
Data Analyst

Health Services and Outcomes Research (HSOR)
National Healthcare Group
3 Fusionopolis Link
#03-08, Nexus@one-north (South Lobby)
Singapore 138543
Tel: +65 6496 6940
Fax: +65 6496 6257
Email: hsor@nhg.com.sg
Website: www.hsor.nhg.com.sg