What input and output variables have been used in models of patient flow in acute care hospital settings?

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Patient flow reflects the capacity of a healthcare system/process to efficiently and effectively deliver care and move a patient through the healthcare system. Improving patient flow has become a central goal of healthcare managers worldwide. Patient flow models have emerged as a sophisticated method to facilitate improvements in patient flow. This report summarizes evidence pertinent to the development of patient flow models, with a focus on key inputs and outputs incorporated in patient flow models in the acute care hospital setting. Its intention is to support the knowledge needs of senior management and other relevant stakeholders considering the development and implementation of a patient flow model in The Ottawa Hospital.

Key Messages

- Patient flow is a concept reflecting the movement of patients through a sequence of processes as part of their pathway of care. Patient flow is considered to be central to understanding key components pertinent to hospital performance (including queues, redundancies, capacity and demand).
- A patient flow model is an attempt to look at care processes from the perspective of a unit, department, or hospital. Patient flow models have been promulgated as tools to "support service improvement at specific bottlenecks or constraints, in specific clinical areas, or across whole health systems".
- Many patient flow models have emerged to date incorporating various theoretical frameworks, statistical methodologies, and measurable inputs and outputs. Patient flow models have also been designed for varying purposes and varying contexts (e.g. generic hospital wide models vs. specific department-oriented models).
- Local stakeholder involvement is considered to be integral to the design and validation of patient flow models. Although implementation (and reporting of implementation) has been poor, some models have led to improved outcomes of patient flow. Further research is required.

Who is this summary for?

This summary was undertaken for The Ottawa Hospital and is intended for use by local health systems stakeholders, policy-makers and decision-makers within The Ottawa Hospital.

Information about this evidence summary

This report covers a broad collection of literature and evidence sources **with a search emphasis on systematic reviews.**

As such, evidence summarized from systematic reviews is highlighted in blue boxes, like this one. Systematic reviews are generally favoured over other study designs, because they incorporate evidence from multiple primary studies, instead of reporting evidence from just one study.

☑ This summary includes:

- **Key findings** from a broad collection of recent literature and evidence sources.

☒ This summary does not include:

- **Recommendations**;
- **Additional information** not presented in the literature;
- **Detailed descriptions of the interventions** presented in the studies.

Many sections conclude with a **"Bottom line"** subsection that provides a statement summarizing the studies or aims to provide some context. These statements are not meant to address all of the evidence in existence on the subject, rather, only that which is featured in this document.

All papers summarized in this document are available by request to kkonnyu@ohri.ca.

I. Background

Hospitals, and in turn hospital managers, face growing pressures to increase the quality and quantity of hospital services using limited resources.[1;2] One strategy to address these challenges is to optimally manage the system's logistics (e.g. hospital processes, resources).[2] Knowing *how* to optimally manage the system logistics however requires tools to understand the systems behavior and predict the outcome of different scenarios[2]. Here, models of patient flow have been proposed as an accurate and effective approach to observe and modify variables related hospital efficiency/patient throughput.[1;2]

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The objective for this review was to conduct a rapid summary of the evidence related to patient flow models – specifically, the input and output variables that have been included in patient flow models. Its aim is to support knowledge needs of senior management and other relevant stakeholders considering the development and implementation of a patient flow model in The Ottawa Hospital.

II. What is patient flow?

Patient flow is a concept reflecting the movement of patients through a sequence of processes as part of their pathway of care. Patient flow is considered to be central to understanding key components pertinent to hospital performance (including queues, redundancies, capacity and demand).[3]

III. What is a model of patient flow?

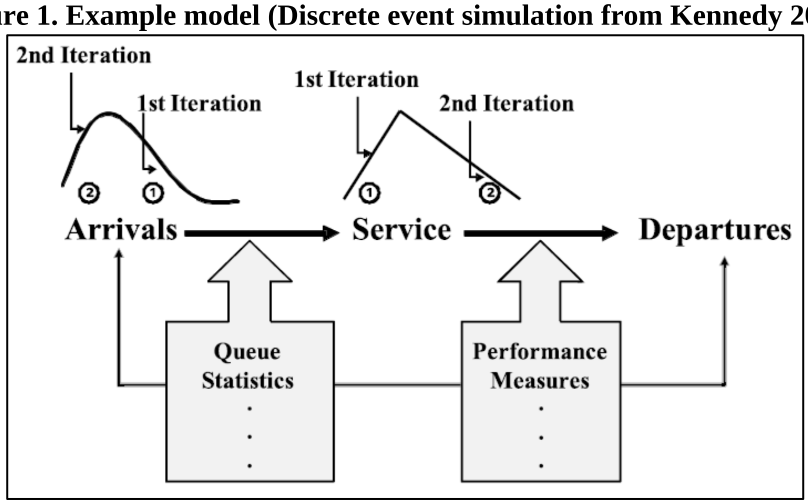
a. Overview

A patient flow model is an attempt to look at care processes from the perspective of a unit, department, or hospital (see example in Figure 1). Patient flow models have been promulgated as tools to "support service improvement at specific bottlenecks or constraints, in specific clinical areas or across whole health systems".[3] Many patient flow models have emerged incorporating various theoretical frameworks, statistical methodologies, and measurable inputs and outputs.[3]

b. Generic vs. specific hospital models

Although a singular, generic hospital-wide model may be desired for simplicity, it has been argued that the "complexity of the hospital organization and the

Figure 1. Example model (Discrete event simulation from Kennedy 2009)[4]



number of different kinds of processes make it extremely hard to generate a straightforward solution" for an entire hospital, and further, any model designed for this level would be so abstract it would result "in information with limited value".[2] This is supported by the Theory of Constraints, which argues that targeting specific 'bottlenecks' processes or departments is the most efficient and effective way to improve flow through an organization.[2]

Fletcher and Worthington devote an extensive manuscript to the topic of generic vs. specific patient flow models and conveniently assess their reviewed models according to these two categories (see below).[5] They also note the important distinction between generic whole hospital models and flexible 'generic frameworks'. The latter appears more commonly in the literature, but refers more to a model's degree of transferability (e.g. to different hospital settings) than its capacity to model an entire hospital setting. Informed by both evidence and a survey of expert opinion, they offer a 'Spectrum of genericity' in which models may exist; although the details of this spectrum are beyond the capacity of this review to report, they offer an in-depth exploration of this topic, particularly with respect to considerations for the purpose, design, and use of models, and would be a key resource for consideration (particularly note manuscript Tables 2-6).[5]

c. Evidence

4/7 A 2010 systematic review by van Sambeek and colleagues in The Netherlands assessed decision-making models for the design and control of processes of patient flow.[2] Specifically, models were evaluated with respect to their capacity to handle various problem types and their usability among managers for decision-making. For clarity of understanding, definitions of the terms used by this review are reported in **Sidebar A**. A total of 68 articles were reviewed, including 10 descriptive models, 27 analytical models, and 31 computer simulation models. While descriptive models were exclusively applied to process design problems, analytical and computer simulation models were applied to all types of problems in relatively similar proportions. Computer simulation models were almost never generic, but rather were designed for use in specific departments including intensive care, laboratory, operating room, and emergency room. Outcome measures most frequently modeled by computer simulation models included: throughput time, waiting times, needed capacity, and utilization (see **Table 1** for data on computer simulation and other models). Unfortunately, most models were not validated in practice, and have not been used for their intended purpose (i.e. to support managerial decision-making). According to the reviewers, the findings of this review "give managers insight into the characteristics of various types of decision-support models and into the kinds of situations in which they are used". Given that this review appears to be the first systematic assessment of this literature and was published quite recently, it is a valuable resource for managers trying to understand patient flow models.

SIDEBAR A:
Definition of terms in van Sambeek et al.[2]

Model: A representation of a real system that gives insight into the system's behavior, with interfaces with reality corresponding with the aim of use.

Classification for problem types:

- **Capacity problems:** What kind and what amount of resources to attract;
- **Process design problems:** Which process steps to make use of and in what order;
- **Scheduling problems:** At which moment to allocate which resources to which patients.

Classification of model types:

- **Descriptive models:** Models that visually or textually represent a solution. A descriptive model is flexible and often easy to understand and use; however, these models lack quantitative, accurate insight in system behavior.
- **Analytical models:** Models that can calculate output measures of interest for fictive scenarios. The advantage is that they are exact and quantitative, but it is usually difficult to interpret their results. In complex processes, they often ignore too many factors to be able to compare their quantitative results with reality.
- **Computer simulation models:** Models that use computer software programs to simulate variations of the real process accelerated, and afterwards show output measures. Computer simulation models are the most accurate model types, because they calculate over time and often take variability into account. The disadvantages are the cost and development time needed.

Bottom line:
Patient flow models have emerged as potentially helpful tools to understand, predict and improve the flow of patient care through the healthcare system. Although they usually focus on specific processes or departments, some hospital-wide models have been developed. The utility and/or appropriateness of these models however, are unclear. A 2010 systematic review of decision-making models for managers assessed patient flow models according to the problems they addressed, the outcomes they measured, and the settings in which they operated. Computer simulation models (emphasized for the purpose of this evidence summary) covered a diverse range of problem types, but were almost always 'specific' models designed to operate in singular departments (e.g. intensive care, laboratories, operating or emergency rooms). The most commonly employed outcome measures in computer simulation models were throughput time, waiting times, needed capacity, and utilization.

Table 1. Relationship between model type and other categories (from van Sambeek)[[2]]

	Model type						
	Analytical		Computer simulation		Descriptive		
	n	%	*n*	%	*n*	%	Total
Department							
Emergency room	4	29	6	43	4	29	14
Imaging diagnostics	1	50		0	1	50	2
Inpatient	8	62	3	23	2	15	13
Intensive care	1	17	4	67	1	17	6
Laboratory		0	1	50	1	50	2
Operation room	8	50	8	50		0	16
Outpatient	4	29	9	64	1	7	14
Radiotherapy	1	100					1
Generic							
No	4	11	31	89		0	35
Yes	23	70		0	10	30	33
Validated							
No	22	43	27	53	2	4	51
Yes	5	29	4	24	8	47	17
Outcome measure							
Utilization	12	48	12	48	1	4	25
Waiting times	7	41	10	59	0	0	17
Needed capacity	6	40	8	53	1	7	15
Cost	7	50	4	29	3	21	14
Throughput time	2	17	9	75	1	8	12
No. of patients	5	63	3	38	0	0	8
Other	9	38	5	21	10	42	24

IV. What input and output variables have been included in patient flow models

A 2009 'extensive literature review' by Fletcher and Worthington of the United Kingdom assessed the characteristics (design, validation, and implementation) of generic and specific flow models for emergency patients.[5] Although this is not a systematic review, it provides a helpful exercise in mapping the major components of patient flow models (including inputs and outputs) across a range of model types used in various hospital settings (**see Table 2**). The review organizes the models according to the specific departments or issues the models were designed to target: Emergency department, Bed management, Surgery, Critical/Intensive care, and Diagnostics. The few models reflecting whole systems or multiple departments are presented last. For reference, the review defines 'black box' as a type of validation "where the model output is numerically tested against known characteristics of the system" and "predictive accuracy is important". In contrast, 'open box' is defined as "a critical assessment of the variables and relationships of the model. Performed in partnership with experts on the system being modeled, it generates mutual agreement that the model accounts for the key 'real world' issues".[5]

Table 2. Generic and specific models of patient flow for emergency patients in a hospital

EMERGENCY DEPARTMENT – GENERIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Fletcher et al. (2007)[6]	DES	To identify barriers to meeting national (England) ED target of having 98% of ED attendances to be completed within 4h	1) Diagnostics 2) Bed management	1) Generic pt flows 2) Process time for each ED process 3) Required resources (staffing)	Yes – against a national survey of ED pt flow	Yes – nationally with key stakeholders to identify main issues and potential interventions; locally with hospitals not meeting the ED target
Sinreich et al. (2004)[7]	Simulation	To be applicable to many ED departments	1) Pts – grouped by TOD of arrival and testing requirements	Unclear	Not discussed	Not discussed
Centeno et al (2003)[8]	Linear programming combined with DES	To reduce staffing cost in an ED	1) Generic pt flows 2) Service time distributions for doctors and nurses at each process 3) Inter-arrival times of pts (estimated by TOD)	1) Optimal resources* 2) Optimal shift patters* * generated using linear programming for different demands	Unclear	Not discussed
EMERGENCY DEPARTMENT – SPECIFIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Takakuwa et al. (2004)[9]	DES	Not explicitly described, but coverage included ED processes and surgery	1) Pts - grouped by type (ambulance, walkins) with assigned routes 2) Resources – clerks, treatment cubicles, medical staff, nurses, and diagnostic rooms	1) 'Congestion factor' 2) Total pt time under different scenarios (e.g. staffing, beds, etc).	Not discussed	Not discussed
Blasak et al. (2003)[10]	DES	To reduce ED pt time, including wait for beds.	1) Pts – grouped by arrival time, type (ambulance,	1) Pt time – by process and total	Not discussed	Yes – reported to have 'directed the change

		Coverage included ED and 'medical telemetry' unit	walk-ins, direct) and urgency 2) Processes/resources – diagnostics, staff (doctors, nurses, healthcare assistants), patient transport, cleaning, rooms, beds, other hospital transfers (in telemetry unit).	2) Queue length by process 3) Utilization of staff, rooms, and beds		process'
Rossetti et al. (1999)[[11]]	DES	To increase pt throughput and optimize staff utilization by altering staff schedules	1) Pt groups 2) Doctors and nurses 3) Beds 4) Diagnostics 5) TOD and DOW 6) Staffing schedules	1) Throughput (arrival and wait characteristics, transport and routing times) 2) Staff utilization (staff service times)	Yes – using computer system and on site data collection, local feedback on model design and results, and comparison with waiting time data	Not discussed
Baesler et al. (2003)[[12]]	DES	To generate recommended staff levels to accommodate demand increases	*Scenarios included demand rises (e.g. pts, testing) and capacity changes (e.g. doctors, rooms, paramedics, reception staff)*	1) Pt waiting time (non admitted) 2) Recommended staff levels	Not discussed	Not discussed
Wiinamaki et al. (2003)[[13]]	DES	To cope with extra demand	1) ED processes 2) Clinical decisions 3) Admissions units	---	Not discussed	Yes – some recommendations were implemented (e.g. extra x-ray space, new triage and less acute beds).
Badri and Hollinsworth (1993)[[14]]	DES	Not explicitly stated	1) Pts –ER activities for 5 pt groups 2) Medical, pharmacist and administration staffing levels 3) ED beds 4) Staff shift patterns (but no explicit incorporation of TOD/DOW)	1) Service time at each process	Yes – through interviews with local experts and comparison of total time data	Yes – recommendations generated by the model were implemented and monitored
Lane et al (2000)[[15]]	System dynamics	To reduce pt time in ED	1) ED processes (incl. testing) 2) Bed management (incl. electives) 3) Doctor utilization 4) TOD *Scenarios included changes in bed capacity*	1) Pt time in ED (esp. admitted pts)	Yes – through discussion with local experts and comparison with data	Not discussed

			and demand patters			
Komashie and Mousavi (2005)[16]	DES	To understand the drivers of pt time. Coverage included medical admissions unit and diagnostics	1) ED doctors and nurses 2) TOD *Scenarios included adding cubicles or staff, and improved admission processes*	1) Pt/process time (average and variability)	Yes – through demonstration to key experts and comparison with KPIs	Unclear
Samanha et al. (2003)[17]	DES	To show the ED process and bottlenecks and assess improvement options to reduce pt time the ED.	1) Testing 2) Bed availability 3) Arrival and process times 4) ED resources (rooms, doctors and other staff) *Scenarios included changed pathways, ED resizing, and fast-tracking of pts*	---	Yes – open box	Yes – the model found that process changes would avoid the need for expansion and the results were implemented.
Mahapatra et al. (2003)[18]	DES	To reduce pt time using a fast-track centre	1) Pt – arrival time 2) Wait time by process and staff schedules 3) ED sections (triage, critical care, intermediate care, diagnostics, follow-up treatment) 4) TOD and DOW	1) Pt flow through triage, assessment, testing, and treatment and discharge/admission	Yes – open and black box methods	Not discussed
Gonzalez and Perez (1994)[19]	DES	Not explicitly stated	1) Resources – doctors and nurses 2) Processes – testing, assessment, treatment, and waits for beds *Scenarios included variations of staffing and pt routing*	1) Pt time 2) Queue length	Yes – open and black box methods	Not discussed

BED MANAGEMENT – GENERIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Bagust et al. (1999)[20]	Spreadsheet-based simulation	To model emergency inpt bed requirements at a hypothetical acute hospital	1) Seasonal and DOW patterns *Scenarios included growths in emergency demand, occupancy levels, LOS changes, resource pooling*	1) LOS 2) Risk of non-admission of emergency pts	Yes – using data from 2 hospitals, however methods were unclear	No – model was developed as a 'discussion tool'
Nguyen et al. (2005)[21]	Algorithm (details not specified)	To model the optimal number of beds in a unit	1) Transfers 2) Refused unscheduled	1) Optimal number of beds in a unit	Yes – on surgery and medicine departments;	---

			admissions 3) Unoccupied beds		led to improved performance of bed allocation	
Gorunescu et al. (2001)[22]	Model using queuing theory	Not explicitly described	1) Costs of refused access, occupied and unoccupied beds	1) Optimal number of beds	Yes	---
Mackay (2001)[23]	Not explicitly described	Not explicitly described	1) Patient type 2) Occupancy 3) LOS (Pts split into short and long LOS)	1) Daily/month occupancy rates	Yes – using actual occupancy data	---

BED MANAGEMENT – SPEICIFIC MODELS

Author (Year)	Type of model	Objective of model	Inputs modeled	Outputs modeled	Model validated?	Model implemented?
Harper and Shahani (2000)[24]	DES	Not explicitly described	1) Arrival and discharge rates (hourly, daily and monthly) 2) LOS 3) Beds by pt 'CART' category 4) Refusal rates (a bed is unavailable in the preferred unit)	Unclear (likely rates of occupancy and refusal)	Yes – using 1 year's data of occupancy and refusal rates	Yes – recommendations have been implemented, including bed requirements (allowing for variability), combining bed pools, pt categorization and admissions policies
Harris (1985)[25]	DES	To model surgery ward beds (pre/post op)	1)Surgery schedules by type of pt and consultant 2) LOS 3) Variability of each pt type *Scenarios included improved theatre schedules and bed management policies*	1) Average and variability of bed requirements	---	Not discussed
Dumas (1984)[26]	--	To improve bed allocation and pt placing policies between specialties	1) Demand 2) Admission processes* 3) Inpt pt movements through to discharge* 4) Specialty level LOSs *Categorized by DOW	1) Specialty level demand and the process of assigning the demand to bed pools 2) Occupancy 3) Misplacements	Yes – through structured discussion sessions with bed managers	Not discussed
Vissers (1998)[27]	---	To model a bed allocation by specialty	1) Projections in demand 2) LOS	1) Optimal bed allocations based on actual use	---	Not discussed

SURGERY – GENERIC MODELS

Author (Year)	Type of model	Objective of model	Inputs modeled	Outputs modeled	Model validated?	Model implemented?
Blake et al. (1995)[28]	DES	To model surgical pt flows through admission, operating theatre, beds and discharge	1) Key characteristics – surgeon, service, age, sex, procedure 2) Key constraints – beds,	---	Yes – using historic data of activity of beds and theatres	Yes – used to justify theatre reduction, adequacy of resources, increased cardiac

			nurses, operating theatre capacity, doctors			surgery and beds in holiday periods
SURGERY – SPECIFIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Lowery (1999)[29]	Simulation	To examine a hospital's theatre capacity	1) Key factors – schedules accounting for specialty, theatre, DOW, arrival time and block start/stop times 2) Surgery downtime (due to staff, pts, equipment) *Scenarios included alternative schedules, extra time and case time reductions*	1) Pt throughput	Yes – model throughput was tested against actual throughput by specialty; results were discussed with surgeons	No
Centeno et al. (2000)[30]	DES	To model theatre and pre/post-operation requirements	1) Procedures 2) Times 3) Probability of cancellation 4) Arrival patterns (characterized by TOD and DOW) 5) Returning pts 6) Costs of personnel, equipment and supply *Scenarios included reduced support, extra theatres and different schedules*	1) Theatre idle time 2) Throughput 3) Waits for theatre 4) Costs	Not discussed	Not discussed
Ramis et al. (2001)[31]	DES	To increase throughput; coverage was pre-op preparation, operation, and post-up recovery and support	1) Resources – beds by area and staffing *Scenarios included extra pt preparation areas*	1) Pt throughput	Yes – using historical data and discussion (unclear with whom – presumably surgeons)	Unclear
Kwak (1976)[32]	DES	Not explicitly stated; coverage included surgery and recovery	1) Pts – categorized by major/minor and specialty 2) Process times (and variability) – in the theatre and recovery rooms *Scenarios included alternative scheduling rules and pt categorization (compared to hospital policy of randomized allocation)*	---	Yes – methods unclear	Yes – hospital management chose and implemented 1 of the strategies

Wright (1987)[[33]]	DES	To assess potential reductions in surgical beds in a regional health district	1) Beds – categorized by hospital, specialty and type (gender, children) 2) Theatre session data (categorized by specialty, major/minor, DOW, TOD) 3) Bed data (incl. emergices/electives per day, LOS pre and post-op, sex of pt). *Simulated theatre sessions were generated using current hospital policy. Scenarios included changes in demand, theatre capacity and beds*	---	Yes – against historical bed occupancy	Yes – to plan responses to bed cuts
Bowers and Mould (2002)[[34]]	DES	To examine a potential expansion of surgery and beds	1) Admission rates 2) LOS 3) Theatre time	1) Distributions of required beds and theatre usage	---	Not discussed
CRITICAL/INTENSIVE CARE – GENERIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Costa et al. (2001)[[35]]	DES	To plan ICU capacity	1) Admission status (elective, emergency) 2) Source (theatre, ED, wards, hospital transfers, others) 3) Specialty 4) Age 5) LOS 6) Number of beds	1) Beds vs. occupancy 2) Deferral rate 3) Transfer rate	Yes – using 'actual' data	Not discussed
Demire et al. (2001)[[36]]	DES	To investigate allocation of surgery time and beds by specialty (incl. ICU)	1) Pre-op surgery preparation 2) Operation time 3) Post-op recovery 4) Beds	1) Throughput 2) Time in system 3) Pts rejected for admission	Not discussed	Not discussed
Ridley et al. (2001)[[37]]	---	Not explicitly stated; method groups ICS pt types using CART	1) Source (e.g. ED) 2) Age 3) Specialty	1) ICU LOS	Yes – tested on 3 hospitals	---

CRITICAL/INTENSIVE CARE – SPECIFIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Griffiths et al. (2005)[[38]]	DES	To identify the optimal number of nurses for a specific ICU	1) Resources – beds, nursing staff 2) Admissions –	1) Nursing requirements	Yes – using data on arrivals, LOS and nurses	Yes – optimal numbers of nurses were generated and

			characterized by DOW and TOD from each route (elective/emergency surgery, ED, ward, other hospital, high dependency unit, X-ray) 3) LOS distributions for each pt type *Scenarios included referral rates, outreach programs and increased demand*			implemented
Cahill and Render (1999)[[39]]	DES	Not explicitly stated	1) Admissions 2) Discharges 3) Diagnoses 4) LOS (in ICU and surrounding units; modeled by diagnosis) 5) Between unit transfers 6) ED activity and delays *Scenarios included the numbers of beds in each unit.*	1) Utilization and service levels	Yes – using historical data on utilization, discharges and LOS	---
Bonvissuto (1994)[[40]]	---	To model ICU bed requirements	1) Occupancy 2) Diagnosis 3) LOS 4) Transfers	---	---	Not discussed
Ridge et al. (1998)[[41]]	DES	To calculate the optimal number of ICU beds to preserve service levels at the lowest cost	1) Pt volumes 2) LOS 3) Number of beds 4) Arrival rates by DOW *Scenarios included number of beds, pt prioritizations, emergency bed reservations, and changed DOW policies*	1) Number of pts transferred due to lack of beds	Yes – using historical data	Not discussed
Kim et al. (1999)[[42]]	DES and queuing	Not explicitly stated	1) Routes into ICU (wards, ED, emergency/elective theatre) 2) Pts (split by specialty) 3) Illness severity 4) Age 5) LOS 6) Probable outcome	1) Pt volumes, arrival rates and LOS organized by route	Unclear	---

Shmueli et al. (2003)[43]	Queuing	To optimize the size of an ICU	1) Wait time for admission 2) Costs of beds	1) Health benefit (undefined) 2) Optimal number of beds	Yes – using computer data	Not discussed

DIAGNOSTICS – GENERIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Ramis et al. (2002)[44]	DES	To reduce pt waiting times across 40+ labs	1) TOD demand 2) Staffing 3) Staff groups 4) Test specific rooms and equipment 5) Staff/test specific service times	1) Pt wait times for diagnostics	Yes – against data and with staff	Unclear
Berchtold et al. (1994)[45]	DES	Not explicitly stated	1) Equipment 2) Staff 3) Demand types 4) TOD/DOW 5) Work planning methodologies	---	Yes	Unclear
DIAGNOSTICS – SPECIFIC MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Couchman et al. (2002)[46]	DES	To model increases in workload	1) Working practices (not specified) 2) Resources – equipment and lab staff (by type) 3) Demand profiles by TOD/DOW *Scenarios included changes in working practices, likely future performance, new instruments and automated handling.*	1) Lab response times	Yes – using lab performance by TOD and discussion with lab managers	Unclear
Ramakrishnan et al. (2004)[47]	DES	To model pt throughput and report generation time with a new service in a CT scan area	1) TOD demand by pt type 2) Resources – radiologists, technologists, clerks *Scenarios included increased machine use and numbers of radiologists*	1) Pt throughput 2) Report generation time	Yes – using data on throughput and report generation time	Not discussed
Van Merode et al. (1995)[48]	DES	To improve laboratory workflows	1) Demand profiles 2) Process times	1) Laboratory workflow (not specified)	---	Not discussed

			3) Technicians			
O'Kane (1981)[49]	Simulation	Not explicitly stated; coverage was a diagnostic radiology department	1) Pt arrival patterns 2) Examination requirements and durations 3) Number and type of rooms 4) Radiographers *Scenarios included numbers of radiographers, streaming by hospital department, room usage, demand changes, and appointment changes.*	1) Mean, max. and min. of pts seen by source/day/week 2) Waiting times and queues 3) Staff and room utilization	Yes	Not discussed

MODELING FLOWS BETWEEN THE ABOVE DEPARTMENTS AND WHOLE SYSTEM MODELS						
Author (Year)	**Type of model**	**Objective of model**	**Inputs modeled**	**Outputs modeled**	**Model validated?**	**Model implemented?**
Pitt (1997)[50]	Simulation modeling framework	Not explicitly stated but designed to be used with a UK health authority covering all aspects of acute health delivery	1) Bed usage and allocations 2) Demographic issues 3) Demand fluctuations 4) Admissions 5) Ward configuration 6) LOS 7) Day case rates	1) Optimal number of beds in hospitals/health authority	Yes – using hospital data	Not discussed
Dittus et al. (1996)[51]	Simulation	To improve doctors work schedules in an acute hospital	1) Model defines generic activities of doctors and assesses allocation of time between them.	1) Doctors schedules	---	Yes

Inpt: inpatient; DES: discrete event simulation; DOW: day of week; ED: emergency department; ICU: intensive care unit; LOS: length of stay; pt: patient; TOD: time of day; KPI: key performance indicator

Bottom line:
An extensive review by Fletcher and Worthington assessed generic and specific models of patient flow for emergency patients. Summarizing the body of literature, the reviewers deem the models to have "similar features of design, data, validation and implementation". Design typically evolved from discussions with local experts and often involved process mapping. Validation usually involved discussions with local experts and comparison of outputs with historical data. Implementation was rare, despite seemingly "good engagement with the local stakeholders in the design, data collection and validation stages".

Table 3. Additional models of interest

Author (Year)	Characteristics of model
Asplin et al. (2006)[52]	Exploration of the concepts of daily surge capacity and its relationship to patient flow, propose 2 models that have implications for both.
Bair et al. (2010)[53]	DES approach was used to model emergency department patient flow to investigate the effect of inpatient boarding on emergency department efficiency.
Brenner et al. (2010)[54]	A simulation model of patient throughput in the emergency department.
Cardoen and Demeulemeester (2008)[55]	Discrete-event simulation tool to evaluate the efficiency of clinical pathways with respect to patient throughput.
Chase (2005)[56]	Development of patient flow modeling in Vancouver; case example of implementation.
Chow et al. (2008)[57]	Present two models (a Monte Carlo simulation model and a mixed integer programming model) to enhance patient flow in a surgical department.
Coats and Michalis (2001)[58]	Design and evaluation of a mathematical model of patient flow through an emergency department.
Côté and Stein (2000)[59]	Presents an Erlang-based stochastic model for patient flow in a healthcare environment.
Creemers and Lambrecht (2008)[60]	Model patient flow of an orthopaedic department using simulation and queuing models.
Creemers and Lambrecht (2008)[61]	Methods paper demonstrating how to construct a queuing model of a general class of health systems.
Ding et al. (2010)[62]	Model of emergency department patient flow using multivariate quantile regression.
Elbeyli and Krishnan (2000)[63]	Model of patient flow using ProModel™ Simulation Package.
Ferreira et al. (2008)[64].	Discrete-event computer simulation model of a surgical department.
Flottemesch et al. (2007)[65]	Development of a model of emergency department census that incorporates concepts of emergency department crowding, daily patient surge, throughput time, and operational efficiency.
Garg et al. (2010)[66]	Discrete time Markov model for admission scheduling and resource planning.
Harrison (2001)[67]	Presents models based on mixed exponential occupancy distributions and discusses their implications for health care planning.
Harrison et al. (2005)[68]	Harrison-Millard multistage model, modeling variability in hospital bed occupancy/patient throughput.
Hoot et al. (2008)[69]	Discrete event simulation model of emergency department patient flow.
Isken and Rajagopalan (2002)[1]	Demonstrates the potential of using data mining techniques to help guide the development of patient type definitions for the purposes of building computer simulation or analytical models of patient flow in hospitals.
Jiang and Giachetti (2008)[70]	Queuing network model modeling patient flow in emergency department.
Kolker (2008)[71]	Discrete event simulation model of emergency department patient flow.
Kolker (2009)[72]	ICU patient flow simulation model.
Laskowski et al. (2009)[73]	Application of agent-based model and queuing model techniques to the operations of an emergency department.
Lattimer et al. (2004)[74]	System dynamics model populated with demographic and activity data to simulate patterns of demand, activity, contingencies, and system bottlenecks.
Levin et al. (2011)[75]	Discrete event simulation model of patient flow in a cardiac surgical and emergency department setting.
Marshall et al. (2004)[76]	Patient flow model focused on outcomes and length of stay for the elderly specifically.
McManus et al. (2004)[77]	Queuing theory mathematical model of patient flow for an intensive care unit.
Ryckman et al. (2009)[78]	Evaluation of a model designed for the intensive care unit.
Shahani et al. (2008)[79]	Simulation model for the flow of patients in critical care units.
Storrow et al. 2008[80]	System-level simulation model to identify important outcome measures to improve emergency department throughput.

V. Additional considerations

A few resources emerged, which although they do not present direct information on inputs and outputs of patient flow models, appear to be excellent tools for conceptually understanding and developing models themselves. These include:

1) **A guide to service improvement: Measurement, analysis, techniques and Solutions**.[[3]] Produced by the Scottish Executive and NHS Scotland, this extremely user-friendly report offers helpful conceptual definitions for process mapping, patient flow and other related concepts and provides how-to tips for developing models and links to further information. Section 2 through 5 are particularly relevant and may be helpful for both senior hospital management and model developers (Section 2: Understanding the patient journey – Analysis; Section 3: Understanding the system – Demand, capacity, activity, and backlog; Section 4: Measurement; Section 5: Queuing theory).
2) **Simulation modeling for the health care manager**.[[4]] This article provides an introduction to simulation modeling, specifically for addressing the problems faced by healthcare managers. Patient flow is presented as one of the problems typically addressed by healthcare simulation modeling. (as well as facility planning, resource allocation, staffing, routing and transportation, supply chain management, and process improvement).

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Methods

Detailed search strategies were developed by an experienced Information Specialist (specific search terms available upon request). Searching was limited to the following databases:

- Biomed Central;
- Cochrane Database of Systematic Reviews (CDSR);
- Database of Abstracts of Reviews of Effects (DARE)
- National Health Service Economic Evaluation Databases (NHS EED)

Search concepts included Medical Subject Headings (MeSH) and non-thesaurus terms (i.e. text words). A 'grey literature' search was also conducted for potentially relevant studies by reviewing the web sites of relevant organizations and professional bodies (available upon request). Screening was conducted by two reviewers; quality assessment and extraction was done by one reviewer.

Based on the complexity, heterogeneity, and magnitude of the records, we chose to only include studies published during or after 2000. In addition, included citations had to have been published in English and be available in full text electronically.

Risk of Bias Assessment of Systematic Reviews

AMSTAR is an 11-item measurement tool created to assess the methodological quality of systematic reviews. Each question is scored according to 1 of 4 options (yes, no, cannot answer, not applicable) and the number of 'yes' answers tallied. A higher score indicates increased methodological quality.[[81]]

The 11 assessment criteria are as follows:

1. Was an "a priori" design provided?
2. Was there duplicate study selection and data extraction?
3. Was a comprehensive literature search performed?
4. Was the status of publication (i.e. grey literature) used as an inclusion criterion?
5. Was a list of studies (included and excluded) provided?
6. Were the characteristics of the included studies provided?
7. Was the scientific quality of the included studies assessed and documented?
8. Was the scientific quality of the included studies used appropriately in formulating conclusions?
9. Were the methods used to combine the findings of studies appropriate?
10. Was the likelihood of publication bias assessed?
11. Was the conflict of interest stated?

Normally the AMSTAR score is out of 11 however we have chosen to report a modified score out of 7 due to the lack of applicability of 4 questions (#7,8,9,10). The modified AMSTAR score (from 0 to 7) for each systematic review in this evidence summary is reported in the box that appears at the beginning of each finding.

Additional Information

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Conflict of Interest
None declared

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