Using AI to build the foundation of better capacity management

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Abstract Operating at optimal capacity is more critical than ever for hospitals and health systems. Sophisticated capacity management allows healthcare organisations to create the right availability in intensive care units (ICU) and floor units, meet demand for elective surgeries and infusion treatments in a timely way, and adjust staff and nursing rosters nimbly to avoid burnout. But why are health systems so challenged to address these issues now, let alone during crises? In healthcare, the foundational math of capacity management, matching supply with demand and linking multiple services, is largely broken. This paper discusses how the healthcare industry can learn much from the successes other industries have achieved in these areas. It will, however, require fundamentally revamping existing tools and processes for health systems not only to overcome capacity shocks like future COVID-19 surges but also to maximise the use of existing assets and create value for patients and the organisation. Essential to delivering value-based care in today's dynamic environment is deploying proven and scalable AI-driven, virtual and distributed systems and creating an organisational culture of innovation that embraces the change. Hundreds of health systems across the USA have already adopted digital transformation solutions that empower them to make real-time capacity optimisation decisions. Results include an 8 per cent decrease in opportunity days (difference between Med/Surg LOS & CMS LOS), US$500,000 more revenue earned per operating room (OR) per year, and significantly decreased patient wait times and increased patient volumes for infusion centres.

KEYWORDS: Digital healthcare, healthcare delivery and systems, transformation, administration and operations, capacity management, throughput, lean

INTRODUCTION: WHY OPTIMISE CAPACITY IN HOSPITALS?

One of the most pressing operational questions facing hospital and health system leadership is 'how do we get more from our existing assets?' Most cost reduction efforts in a health system are focused on reducing labour expenses or negotiating for lower prices on drugs and supplies. Depreciation of capital, however, typically represents 15–25 per cent of a US health system's total expense and should thus be considered as a priority for cost reduction as well. These health systems buy and build as much patient capacity as they can afford and then, like freeways that are constantly in rush hour, operate at the very edge of that capacity. A shock to the system on either the demand or the supply side will push the health system into a state of chaos and gridlock.

The COVID-19 pandemic was an illustrative shock to the demand and supply sides of health systems alike. On the demand side, tens of thousands of people in a small geographic area suddenly needed intensive medical care. On the supply side, supply chain disruptions led to shortages, first, in personal protective equipment (PPE), then ventilators, then ICU beds, then regular inpatient beds and, finally, for nursing staff — all exacerbated by the influx of patients needing life-saving care.[1]

Further, the crisis placed enormous financial pressure on health systems, as elective cases were deferred, and a reduced number of procedures, in turn, led to reduced reimbursement.[2] With patients now returning to care, compounded by an increasingly aged population[3] with a higher incidence of chronic health conditions,[4] systems need more capacity but can no longer afford to buy it. The historical approach of building and buying more capacity is too costly. The 5,000 hospitals in the USA have already spent, in aggregate, over US$2tn in healthcare assets like ORs, infusion centres, robots and imaging machines.

Clearly, the healthcare industry must shift from building more assets to getting more out of existing assets that are already available but so far unable to be fully used. The unfulfilled potential use of these assets is often apparent in day-to-day functions, for instance:

- In ORs, surgeons are frequently unable to access the time they need to perform cases, and yet rooms and specialised equipment like robots sit unused.
- Nurses at outpatient infusion clinics are overwhelmed by an influx of patients at midday peak hours between 10am and 2pm, but chairs and appointment times go unused in the mornings and afternoons.
- Hospital staff rely on intuition, manual lists and constant meetings to direct incoming patient flow among available beds in appropriate units as best as they can, while patients in intensive care units (ICU) or post-anaesthesia care units (PACU) occupy needed beds long after they should be discharged or moved to a floor unit.

These are supply-demand problems. Other industries driven by similar tension have aligned their fundamental operations to overcome equivalent challenges with great success. By bringing the same level of analytic rigour to its operational workflows as other industries do, healthcare can achieve similar results.

Consider the operational and financial impact of successfully optimising capacity in healthcare. The total value at stake is US$200–250bn per year across all 5,000 hospitals in the USA, which translates to US$40–50m per year for the average hospital. It also manifests in the growing value of specific assets.

- A single OR is worth US$500,000 per year when utilised fully, and ORs generally account for 40 per cent of revenue and half of operating income for a US hospital. Improving the utilisation of ORs by 5–6 percentage points allows more surgeries to be completed each day, thereby creating tens of millions of dollars of value each year for hospitals with 20 or more ORs. Surgeons are also better able to access the time they need to perform cases and clear their backlogs, while surgical nurses and staff can perform their work more efficiently.
- An infusion chair can generate US$20,000 of additional revenue annually. Unlocking 10–15 per cent extra capacity in infusion centres has added US$1m of value per year for oncology practices with 50 or more infusion chairs. Nurses can work consistent, efficient schedules that allow them to take breaks and focus on their patients, while wait times for at-risk patients, whose time is precious, are reduced by 40–50 per cent.
- Each and every inpatient bed in a hospital can be worth US$9,000 per year, when occupied by the right patients at the right time. Staff can better fill beds when they are able to forecast and predict the likely sources of inpatient population from day to day and proactively clear discharge barriers before they lead to backlogs.

Currently, as healthcare providers face an ongoing shortage of clinical providers and staff and while the reimbursement system rewards the performance of an increased number of services, the ability to do more with existing assets is critical.

The foundations of capacity management: A deeper dive and a higher level of math

Solving the capacity management problem in healthcare requires understanding and appreciating two important concepts: matching of supply and demand and the linking of multiple services.

Concept 1: Making a fundamentally fixed supply fulfil a volatile demand

The demand for each specific service provided by a health system, such as surgery, inpatient treatment, specialist appointment, infusion and imaging, is volatile and therefore hard to predict. The amount of time needed to provide each service is variable and dependent on the provider and the patient. In addition, patients are sometimes delayed because prior services run longer than planned. Hence, the demand 'signal' at any point of time for today, or any day in the future, is highly uncertain.

Meanwhile, the supply of capacity is interconnected, constrained and hard to predict. To deliver any healthcare service, the equipment, the staff and the facilities must be simultaneously available at that exact moment in time. There are a finite number of needed rooms, staff and pieces of equipment, which cannot be changed. At the same time, hospital staff members can call in sick, equipment can break down and rooms can be unavailable at short notice. Hence, the supply signal for those fixed numbers of assets can still be highly uncertain (Figure 1).

Because they are not aware of the complexity of the math involved, or because it appears too rigorous to solve, health

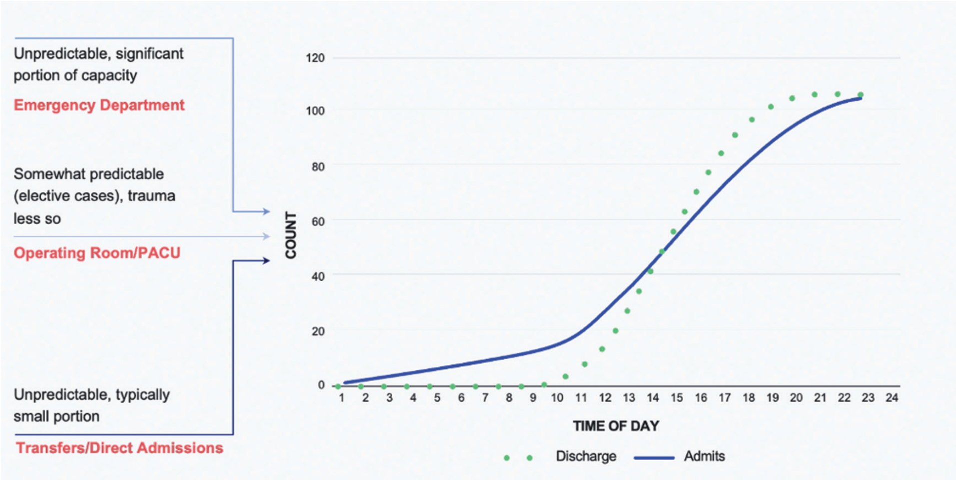

Figure 1 Continuous mismatch of supply and demand

systems have largely ignored the need to find a solution for matching supply and demand signals throughout the day. Instead, they have continued to rely on simple calendaring methods or manual allocation techniques. For example, OR committees generally attempt to solve the challenge of OR scheduling by giving blocks of time to surgeons and service lines based on average utilisation patterns. Averages, however, are not precise math and do not accurately reflect the surgeons' true needs or availability. If a person's head is in the oven and their feet are in the freezer, their average body temperature still reflects a comfortable range; likewise, a neurosurgeon who needs 8 hours of contiguous block time to complete one case and an orthopaedic surgeon who needs 8 hours to complete three cases may have different block utilisation, yet both used their time as efficiently as possible. This imprecise math is compounded by the unpredictable demand by patients who need procedures, meaning that their cases must often be assigned as emergency add-ons as they arise or else delayed. To match surgical supply more accurately with demand, advanced math is required to address the complexity.

It takes sophisticated algorithms to dynamically find the equilibrium between demand and supply signals throughout the hospital every day, throughout the day — particularly since these signals are highly uncertain and vary across services. First, the demand signal must be accurately predicted in terms of the number of patients, the type of treatment they require, the duration of the treatment, and the probability they will be early or late. Next, the availability of the resources needed for a specific service must be determined using constraint-based optimisation algorithms.

In the OR example provided, sophisticated data science can be used to analyse surgeon usage patterns to identify large, contiguous blocks of time left unused, blocks that were abandoned at short notice and blocks that are consistently being released. To support more precise equilibrium in the supply-demand balance, surgeons, service lines and schedulers need a marketplace to request and release times based on the visible ebbs and flows of their patient demand over the coming weeks. This can be augmented by an artificial intelligence/machine learning (AI/ML) agent to predict the likelihood of a surgeon underutilising their blocks in the future and proactively alert them to suggest they release time to accommodate demand from other surgeons.

Left unchanged, the broken math underlying many capacity management processes leads to reduced access for patients and cognitive burden on staff. As a result, the patient and provider experience diminish as they both encounter bottlenecks at various points in the day for virtually every point of contact or service. The cycle repeats itself every day without fail and raises flags for potential diminished quality of care.

Concept 2: Linking discrete services

Each patient experiences a sequence of individual services as part of a single encounter within the health system. For example, the patient may get their blood drawn in the lab, see their provider for a check-up and then get a procedure or treatment done once the provider has deemed it safe. Alternatively, the patient may enter the system through the emergency department, undergo a series of diagnostic tests and then get admitted into an inpatient unit for appropriate treatment and care.

Each of these independent services is like a node in an interconnected network. Each patient travels through a unique set of nodes to receive their required treatment. Optimising the flow across an interconnected network of nodes involves the science of topological network analysis, directed acyclic graph (DAG) theory and other esoteric mathematical methods (Figure 2).[5]

While some health systems have made a special effort to simplify patient flow, for example by keeping a patient in one room or bed where all services can be performed, many others have largely ignored the complexity out of necessity. Instead, patient itineraries are created by 'inspection' — the scheduler simply schedules the individual services as if they were totally independent of each other and prints out the schedule for the patient. As a result of ignoring the connected interdependency between the individual services, patients are often stuck in waiting rooms between the various services that must be completed as part of their treatment visit.

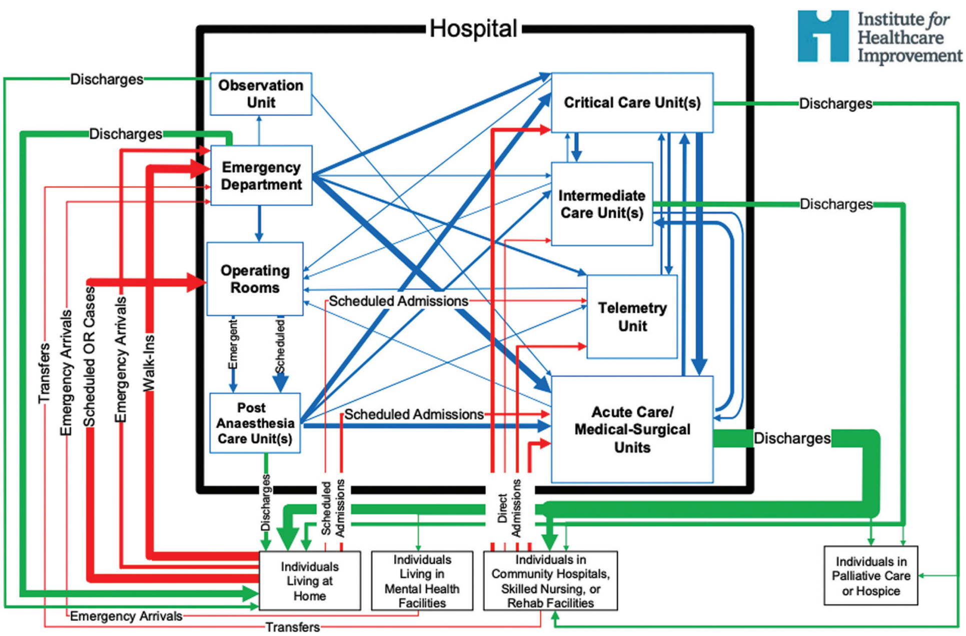

Figure 2 System map of hospital-wide patient flow

The approaches that health systems have deployed thus far involve surface-level, manual solutions for foundational problems that require high-powered math to solve. Simply scheduling an OR or clinic appointment or assigning a bed to a patient, even with comprehensive data on patient history and current capacity levels, is destined to fail. This cannot account for the many stochastic factors involved in that patient's placement and needs, which may change rapidly, along with the intersecting changes in other patients' uses of the same resources and the scheduling of the resources themselves. To do so, health systems must begin to apply the higher levels of math described previously, which simply cannot be applied manually.

How healthcare can solve for capacity management

While health systems have invested millions of dollars in their customized workflows, many are not equipped to perform the level of advanced analytics needed to successfully manage capacity.

Hospital workflows, which include the customization of processes and software, track and display only what has already occurred, and, therefore, they can only allocate resources for the present or future on a first come, first served basis. They do not provide any of the sophisticated mathematical methods like prediction, simulation, optimisation, AI or ML required to dynamically address the ongoing supply-demand balance throughout each day or to view and adjust for the changes in linked services.

In short, workflows may provide some form of analytics but only enough to see capacity problems or assess why they happened, not to forecast and proactively solve problems.

Progressing on the analytics spectrum

Analytics solutions generally range from those that admire problems to those that prescribe actions to create value. Workflows generally fall to the left of this spectrum, while health systems must move to the right to manage capacity successfully. Health systems and their frontline personnel need predictive, prescriptive guidance to make decisions each day based on a nuanced understanding of the ever-changing dynamics of the supply-demand balance (Figure 3).

Descriptive analytics admire a problem. EHRs may provide multiple instances of descriptive analytics in the form of dashboards and reports, and health systems may also rely on those from Excel, Tableau and manually calculated lists. These tools only document capacity issues that already occurred, such as showing which surgeons did not schedule OR time that week,

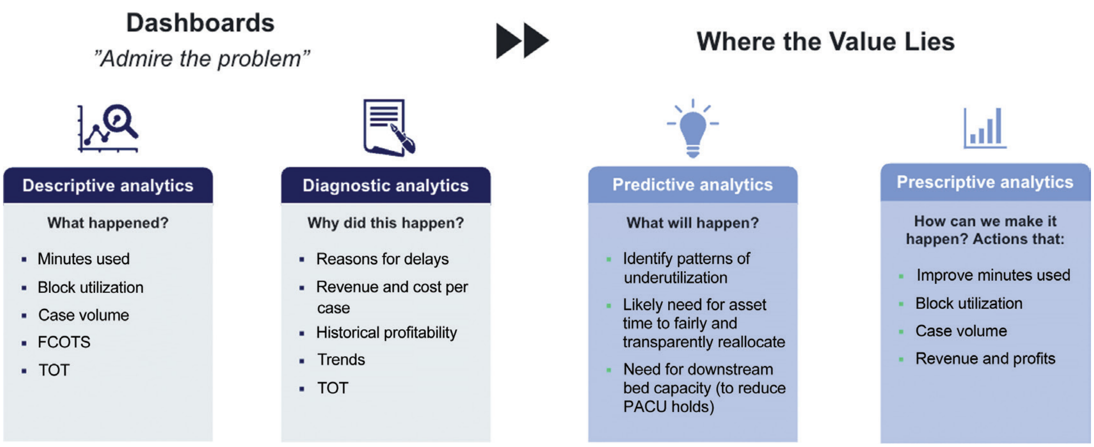

Figure 3 Progression in an organisation's analytics maturity

rather than showing why those surgeons did not schedule time or what would make scheduling easier.

More advanced workflow solutions may further provide *diagnostic analytics* in their dashboards, which slice and dice or deep dive into past data. These are helpful for understanding a capacity issue that occurred yesterday, such as analysing the bottlenecks in a clinic that delayed patient appointments for hours, but they cannot offer a way to pre-empt a similar situation in the future.

The real power of analytics becomes apparent in the ability to forecast meaningful future events. *Predictive analytics*, which deliver specific information about likely future occurrences, help providers, leaders and staff to effectively plan their actions in order to proactively solve problems and optimise opportunities. An OR scheduler, for example, can thus predict which surgical block owners will not fully use their time and which non-employed surgeons could be assigned the remainder to increase OR utilisation.

The most useful analytics, however, are those that drive high-value action, and these must show providers and staff the most powerful solutions. *Prescriptive analytics,* considering both the likely future and the optimal use of resources available in it, will let a surgical department or outpatient clinic alter staffing patterns for a future day or peak time when a surge in volumes is predicted or to proactively 'flatten the peak' and rearrange existing supply to accommodate increased demand from patients.

With their complex and constantly shifting network of services, resources, providers and patients, health systems need both predictive and prescriptive analytics to match supply with demand and link appointments across service lines. Healthcare, as an industry, has yet to widely apply these analytics to manage and optimise capacity, but other industries driven by similar factors provide useful examples of how these same principles work in practice with great success.

Approaches to solving capacity management problems outside healthcare

Logistics and package delivery companies like FedEx and UPS have encountered the problems of matching and linking for decades. They have built sophisticated models and operating practices that allow them to thrive despite the inherent complexity of their business models.

Specifically, it is impossible for them to predict, on any given day, the millions of people across the country who will decide on that very day to ship a package from Point A to Point B. Meanwhile, their 'supply' of resources, including aircraft, trucks, trailers and vans, are constrained and captive within a limited geographical radius. They have to build robust demand forecasting models and design their network of hubs to be flexible and resilient to a volatile demand signal. Once a package delivery van has been loaded, the driver must make as many as 100 stops during the day to drop off and pick up packages. The route they follow is an optimised traversal sequence across the stops they make that must be dynamically rebalanced based on the specific addresses of the packages that happen to be on the van that day. Yet they are able to fulfil their delivery time obligation 99.9 per cent of the time, day after day.

Further, ride-sharing services like Uber and Lyft cannot be certain of the demand on any given day since users decide on the spur of the moment that they would like a ride from Point A to Point B. Yet these services must be able to direct available supply, a car and its driver to any street corner of any major city in the world at any time of the day within a relatively short time interval (eg 10 minutes). They cannot simply look at a calendar and the available roster of drivers on duty to make assignments. Instead, they build sophisticated demand forecasting models based on time of day, day of week, seasonality, weather, zip code, events, etc and then marry it with a deep understanding of the driving patterns of their drivers, who are not employees and whose availability is even less predictable than that of healthcare personnel. Importantly, when supply and demand are not in equilibrium, the ride-share platform actively intervenes in real time by offering incentives to bring more drivers on the roads, surge pricing to defer demand by 30–45 minutes or by issuing automated text messages to reposition drivers closer to where the current demand is located.

Major airlines face a similar challenge in balancing supply and demand at each of their major hubs. They must execute the turnaround of hundreds of aircraft on arrival at a gate and push it back out for another flight within 45 minutes. They do this safely and correctly thousands of times each day. Turning around an aircraft requires linking together dozens of independent services, including baggage handling, cabin cleaning, crew changeover, passenger boarding and catering.

Airlines also have sophisticated models to match the demand for each service (eg baggage handling) with the availability of the supply, including equipment like tows, tugs, ramps, etc and personnel within each section of the terminal. This matching has to take place in a tightly defined zone since it is difficult to reposition equipment across the vast expanse of a major airport, which can easily be 5–6 miles from one end to the other. Furthermore, they have mastered linking services in the right order to maximise efficiency. For example, the cabin can only be cleaned after incoming passengers have left the plane, but it must be cleaned before new passengers board the plane. Notably, airlines also have critical safety and security concerns, and they must factor essential routine maintenance and strict staffing guidelines into their capacity management.

The success of this approach is remarkable. The number of 'aircraft movements', take-off or landing at a major airport over the last 20 years has increased five to tenfold, although the number of runways has remained largely the same. Airline safety failures are also vanishingly rare.[6]

Healthcare, similarly, concerned with precise safety measures, can accomplish the same results. The industry can learn from the models applied by logistics companies, ride-share services and airlines. Some health systems have begun to apply predictive and prescriptive analytics models to their operations. In doing so, they have achieved stunning increases to their existing capacity.

Deploying predictive and prescriptive analytics in healthcare and cases of capacity management success

Leading health systems that have applied high-level analytics to the data they already have, to identify and precisely target their unique capacity problems, provide further illustrations for systems struggling with capacity management. Tapping into knowledge provided by IT platforms that further develop their data sourced from EHRs, these systems determine where to take action, or which 'levers to pull', to improve census predictions and real-time decisions about OR capacity, staffing, surges, discharge barriers, diversion prevention and patient placement. In doing so, they have produced noticeably positive results.

Case 1: Baptist Health, Jacksonville, deploys analytics to OR scheduling for higher utilisation

A not-for-profit integrated delivery network of five hospitals, Baptist Health, Jacksonville, consists of more than 1,000 licensed inpatient beds, six ambulatory surgery clinics, 74 ORs, 14 endoscopy suites and a Level 1 trauma centre. Baptist performed about 47,000 surgeries in 2021 and has a combined 12,000 employed and community physician partners over more than 60 specialty areas.

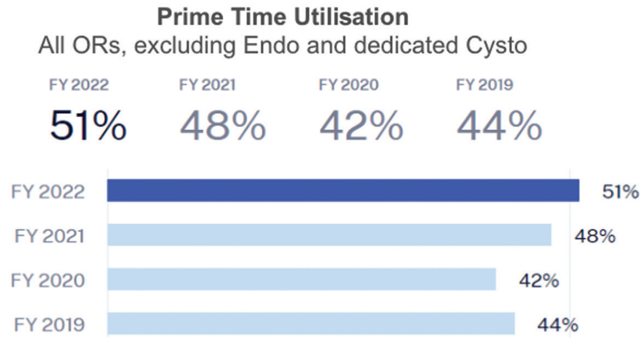

Figure 4 Supply-demand matching enabled Baptist Health to increase OR productivity 16%

With so many surgical spaces and service lines, and employees and patients needing access to them, managing OR utilisation at Baptist was naturally a complex process. Their existing scheduling technology lacked the predictive and prescriptive capabilities needed to staff and assign ORs optimally. Despite consistently low prime time utilisation, surgeons had difficulty reserving the OR time they needed and a perceived need to buy more specialised equipment like robots was belied by records of low usage. Growth in Baptist's surgical areas was stifled, and they were unable to reach financial goals.

To match the often-idle supply of OR time and resources with a clearly surging demand for it, Baptist applied predictive and prescriptive analytics tools to its existing scheduling software. This provided high-quality, centralised OR usage data to all stakeholders who needed it and flagged the most recent occurrence of unused block time and when it could be optimally released and reserved. Surgeons were then able to make full use of the supply available to them.

Results at Baptist Health, Jacksonville:

- Prime time OR utilisation improved enterprise-wide by 16 per cent, or a seven-percentage point increase over prior periods.
- OR scheduler productivity improved, enabling schedulers to book four additional cases per hospital per day through a standardised, streamlined and convenient clinician engagement and scheduling process, which allowed for the flexing of staff across the system (Figure 4).

Additionally, the health system was able to delay significant capital expenditures on ORs and robots that it previously thought were needed to address surgical volume.

Case 2: Hartford Hospital Cancer Institute uses analytics to balance infusion schedules for efficient chair capacity

The Hartford Hospital Cancer Institute (HHCI) is part of the five-hospital, Connecticut-based Hartford HealthCare System. In 2015, HHCI became the first member of the Memorial Sloan Kettering Cancer Alliance. Managing over 8,000 cancer cases per year, HHCI comprises 10 medical oncology practices and 13 infusion centres across the state of Connecticut, the largest of which is the 32-chair centre at Hartford Hospital.

All HHCI's busy infusion centres experienced issues with effectively level-loading patient appointments throughout the day, with bottlenecks at midday peak hours. Despite a significant length of non-peak time going unused, during which chairs sat idle, staff and managers were challenged to accommodate their high number of add-on patients. The need to link infusion treatments with required radiation

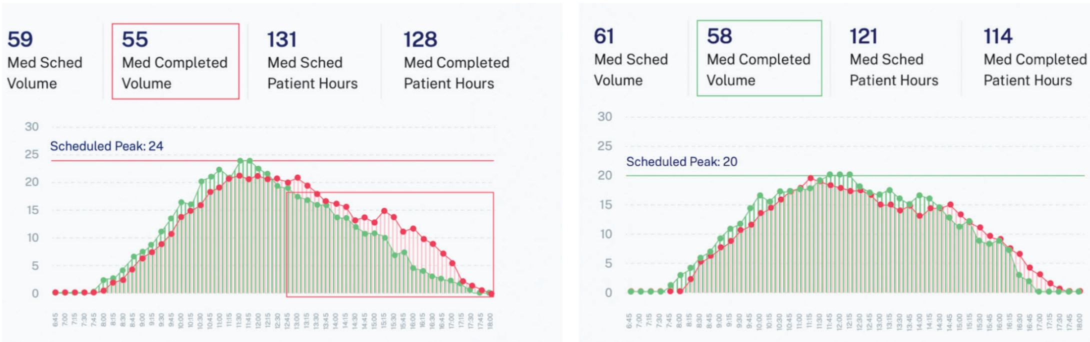

Figure 5 HHCI used analytics to build schedules that aligned with daily demand and patient flow

and medical oncology services further complicated scheduling. This unbalanced capacity use led to nurses having to work through their lunch breaks during peak hours and to long wait times for patients who had linked provider appointments.

HHCI applied advanced analytics to support level-loading days, offering frontline staff data-driven huddle boards and templates, so they could see where bottlenecks were likely to occur in their centre and how to adjust scheduling and appointment linking to clear them in advance. The data also allowed staff and leaders to offer specialised optimal appointment times to individual patients, with the promise of reduced wait times, and helped accurately balance the patient load among nurses based on factors of acuity and appointment length.

Results for HHCI

In its first year of using analytics from 2020 to 2021, the infusion centres comprising HHCI saw an overall 8.9 per cent increase in maximum chair occupancy, despite COVID-related reduced capacity. In the first 18 months, HHCI also achieved the following:

- Increased average daily completed volumes by 10 per cent
- Decreased average scheduling lead days by 14 per cent
- Decreased average patient wait times by 27 per cent

Importantly, HHCI nurses are now regularly able to predict and manage their workloads, take lunch breaks and finish shifts on time (Figure 5).

Case 3: UCHealth empowers staff to align capacity with upcoming inpatient demand

UCHealth is a 12-hospital Integrated Healthcare Delivery System that serves Colorado, southern Wyoming and areas of Nebraska, consisting of 1,997 inpatient hospital beds and performing over 141,000 admissions and observation visits per year.

In attempting to manage their high volume of unpredictable inpatient throughput, UCHealth's bed staff used labour-intensive, manual tools like lists, spreadsheets and dashboards, while also relying on their own experiential knowledge and intuition. While these managers and frontline workers had plenty of data available about which levels of care units needed to be opened and staffed to accommodate patient flow, their reports could not provide the timely and accurate information they needed to predict and make confident decisions about upcoming patient placement and discharges. As they tried to match rapidly shifting and unpredictable demand from patients with supply of beds and align the many disparate services involved in admissions and discharges, inpatient providers and staff existed in a constant state of chaos and were prone to burnout.

Burnout has long been a concerning condition among US healthcare providers, compromising their ability to deliver care safely and efficiently. The 2018 literature review 'Physician burnout: contributors, consequences and solutions' concluded that burnout, 'a work-related syndrome involving emotional exhaustion, depersonalisation and a sense of reduced personal accomplishment', was globally common at that time. Further, the studies reviewed showed burnout symptoms at a prevalence rate of 50 per cent or higher in US physicians, with ensuing consequences such as medical errors and malpractice costs.[7] Burnout has since become a critical problem with the onset of COVID-19, as healthcare workers exposed themselves daily to the virus and cared for an influx of patients despite limited staff and supplies like PPE, ventilators and hospital beds. A survey by Mental Health America reported that almost 77 per cent of its 1,100 healthcare worker respondents experienced burnout during June–September 2020,[8] and in the years since then this problem is now compounded by a workforce shortage.

To better support its inpatient personnel, as early as February 2020 UCHealth adopted predictive and prescriptive analytics solutions that could share bed capacity status updates, predictions on where surges or discharge barriers were likely to materialise, and recommendations for corrective actions across hospitals and the system. Using this centralised and accessible information, staff were able to make decisions and take effective action quickly, moving from reactive chaos management to proactive strategising with a clear impact on capacity. Staff more accurately matched supply to demand, ensuring the right beds were open to the right patients and developing systems of contingency units where they saw a need, and addressing services that the analytics showed needed to be linked for upcoming discharges.

Results at UCHealth

- Decreased time to complete ICU transfers by 65 per cent
- Decreased time to admit from the emergency department by 10 per cent and overall time to admit by 16 per cent (despite an 18 per cent increase in the COVID-19 census)
- Decreased opportunity days (differences between medical/surgical length of stay and CMS length of stay) by 8 per cent, for an approximate US$8m value
- Increased confidence in critical capacity decision making from 50 per cent to 90 per cent

UCHealth also saw a steady decrease in their overall Vizient length of stay index, placing them in the top 25 per cent of the Academic Medical Center cohort in Spring 2022 (Figure 6).

CONCLUSION: OPTIMAL CAPACITY MANAGEMENT IN HEALTHCARE IN THE FUTURE

Health systems that are adopting sophisticated AI-based analytics to address capacity management are successfully optimising their assets and operational performance, leading to significant financial value. In creating a more seamless and efficient experience for patients, providers and personnel, optimised capacity management can increase care access and empower staff while adding tens of millions of dollars to the bottom line.

The ultimate vision is to see every asset within a health system optimised — from ORs, infusion centres and inpatient units to emergency departments, clinics, pharmacies, labs, imaging and more. Every leader in every care setting can have the tools they need to forecast and address underlying problems and thus increase the capacity of all assets across an entire unified, symbiotic system. Simply recognising the mathematical root causes of capacity challenges today, and taking

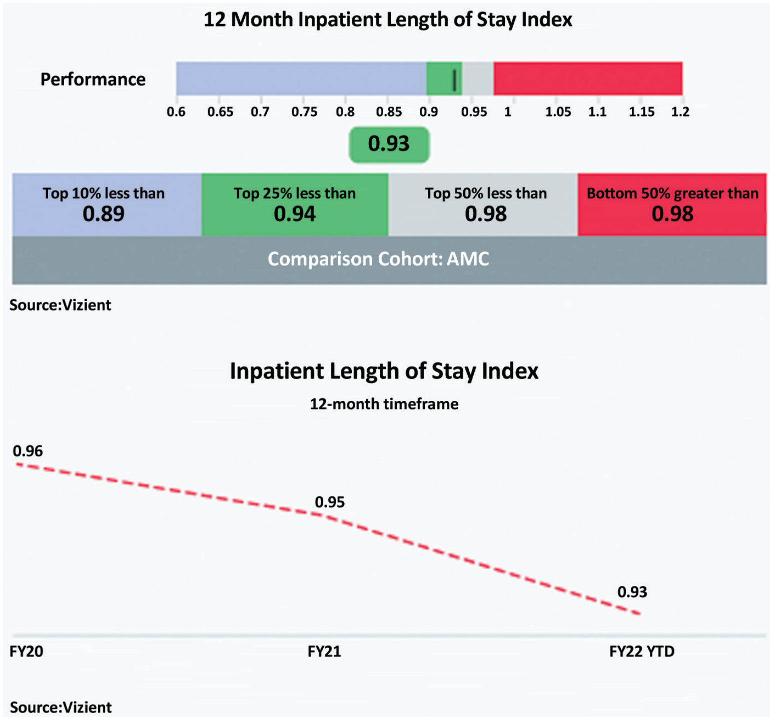

Figure 6 UCHealth experienced a steady decrease in their Vizient length of stay index by deploying AI-based inpatient management tools

informed steps to address them with AI, will make this future more attainable.

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