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How can operational research make a real difference in healthcare? Challenges of implementation

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A B S T R A C T

This paper is based on the keynote address given by the paper's first author at EURO 2021. We draw on our experience over more than three decades to define the critical challenges of healthcare implementation. We do not address issues pertaining to technical quality of a solution. Rather, we focus on five general characteristics of the problem that should be carefully considered for any healthcare project that requires implementation. The problem needs an internal Champion; there should be a current Critical Issue; one must understand and adapt to the Cultural dynamics of the organization; appropriate Data exists; and we need to manage Expectations. We illustrate each with examples of our successes, failures, and mixed results. Finally, we summarize what short and long-term steps we believe the operational research community can take that will lead to improvement in each of these areas.

1. Introduction

Healthcare offers many opportunities for improvement through operational research. However, while there is a great deal of literature on operational research (OR) applied to healthcare including multiple reviews over the years (Klein et al., 1993; Wilson, 1981; Smith-Daniels et al., 1988; Arisha & Rashwan, 2016; Bhattacharjee & Ray, 2014; Brailsford & Vissers, 2011; Brailsford, Harper, Patel & Pitt, 2009; Davahli et al., 2020; Fakhimi & Probert, 2013; Fone et al., 2003; Gunal & Pidd, 2010, Vanberkel et al., 2010; Hulshof et al., 2012; Jun et al., 1999; Katsaliaki & Mustafee, 2011; Mielczarek & Uziałko-Mydlikowska, 2012; Rais & Viana, 2011; Roy et al., 2021; Zhang, 2018), there is also a shared and consistent concern that evidence of successful, impactful implementation is lacking (Bowers et al., 2012; Brailsford, 2007; Brailsford & Vissers, 2011; Brailsford, Harper et al., 2009, 2013; Eldabi, 2009; Fone et al., 2003; Forsberg et al., 2011; Jahangirian et al., 2012; Jun et al., 1999; Katsaliaki & Mustafee, 2011; Lagergren, 1998; Lame et al., 2020; Naseer et al., 2009; Wilson, 1981) even as the volume of published work increases (Davahli et al., 2020; Fakhimi & Probert, 2013; Gunal & Pidd, 2010; Katsaliaki & Mustafee, 2011; Roy et al., 2021). Operational research literature in healthcare is often either intentionally theoretical (Brailsford, Bolt, Connell, Klein & Patel, 2009; Eldabi, 2009) or, if grounded in a practical problem, lacks documentation on the implementation and final impact (Brailsford, Bolt et al., 2009; Fone et al., 2003; Katsaliaki & Mustafee, 2011; van Lent et al., 2012). In addition, most literature describes small, local, incremental operational improvements, rather than systemic, strategic, or tactical level changes (Brailsford, 2007; Gunal & Pidd, 2010; Jun et al., 1999; Vanberkel et al., 2010).

It has been proposed that the impact may be more significant than the literature portrays for a number of reasons: publication may occur prior to final implementation; final impact may be difficult to precisely detect due to simultaneous organizational changes or implementation delays; additional factors may be considered in a final decision; and theoretical impacts may be favoured for publication over practical impacts. (Bowers et al., 2012; Brailsford, 2005; Fone et al., 2003; Katsaliaki & Mustafee, 2011; van Lent et al., 2012; Wilson, 1981). In fact, van Lent et al. (2012) show that implementation rates went from 18% to 44% when comparing implementation reported in the literature to that reported in a post-publication survey. In addition, "soft" applications of OR that many practitioners agree hold great value (Baldwin et al., 2004; Bowers et al., 2012; Eldabi et al., 2002,; 2007; Lagergren, 1998; Robinson, 2001) may not produce a concrete quantitative recommendation for direct implementation but may still help stakeholders understand the complex system within which a decision must be made. Eldabi (2009) explicitly calls for success to be redefined and that we should seek "resolution rather than a solution and a consensus rather than optimization" (p 1835), suggesting that a rigidly defined idea of what constitutes implementation may be inappropriate in judging the value of healthcare modeling. However, the impact of both hard and soft OR lacks rigorous evaluation of intervention success (Lame et al., 2020; Monks, 2016). Finally, there is healthcare operational

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research work being implemented outside of academia that does not appear in the literature (Brailsford, Harper et al., 2009).

Ultimately, although the literature may underrepresent the degree to which operational research work is impacting healthcare, there is still a lot of room for improvement, and it is clear that operational research in healthcare is not yet realizing its potential. Given the state of healthcare systems across the globe, there should be a larger role for OR in transforming care. So why has this not occurred? Why is it such a challenge to have a large-scale impact?

Some challenges facing implementation of operational research models in healthcare are shared with those challenges found both in other applications of OR and in innovation implementation in general, while others are unique or exacerbated in the healthcare setting (Eldabi, 2009; Tako & Robinson, 2015). We therefore draw on insights published by other academics on implementation of OR in healthcare and our own decades of experience applying operational research in healthcare organizations. The literature contains dozens of recommendations and checklists of do's and don't's for successful OR projects (e.g., Brailsford et al., 2013; Frambach & Schillewaert, 2002). These are all valid, but perhaps a little dry and difficult to remember. We would like to propose a short list of five key challenges that every OR implementation should be aware of from the beginning. We intentionally omit the challenges around the design and development of the robust solutions and focus on five broad elements to consider for a successful implementation of healthcare operational research. We will discuss each element, and add examples from our experience, that describe positive, negative, and mixed impacts on implementation success. Our five identified elements are: a Champion, a Critical Issue, Cultural Insight, Data quality, and Expectations management. If one or more of these elements are weak or missing, as may often be the case, extra care will need to be taken to compensate for this risk to implementation success.

2. Champion

It has long been recognized in innovation and implementation studies that the success of a great idea requires a champion to turn that idea into a successfully implemented innovation (Howell & Higgins 1990). We have certainly found this to be the case, and it is often cited as a key success factor among other operational researchers in healthcare (Brailsford, 2005; Brailsford, Bolt et al., 2009,; 2013; Harper & Pitt, 2004; Jahangirian et al., 2015). As a matter of practice, when working in healthcare institutions, we always seek out clinical/healthcare partners to support implementation success. If the champion is missing or ineffective, implementation becomes far more challenging and uncertain. Champions will act as the advocate for the project internally, manage organizational politics, understand legitimate barriers and trade-offs, and offer credibility for the project to colleagues. Howell et al., and Higgins (2005) have shown that the key attributes of a strong champion include "expressing enthusiasm and confidence about the success of the innovation, persisting under adversity, and getting the right people involved" (p. 641)

In addition to the short-term impact on the project at hand, champions can also help to build long-term trust for future projects. Senior management can serve as strong champions (Jahangirian et al., 2015) as they are best suited to securing needed resources and removing obstacles, but effective champions can also include a respected clinician, or manager who can effectively bring colleagues on-board and provide useful insights. We have also seen that the reach of operational research is highest when opinion leaders and decision makers at the national or regional level can be engaged as advocates (Barlow & Bayer, 2011; Brailsford, 2007; Brailsford et al., 2013).

Additionally, embracing and spending time getting skeptics to understand the value of operational research rather than simply trying to "manage" them can pay large dividends as sometimes the converted skeptic will then become a highly effective champion, bring others along, and give them permission to get involved. We have experienced this on multiple projects. For example, when working on a cardiac surgery scheduling model, we worked with a skeptical surgeon to show him how the model could help him meet his goals. He then took on the role of defending the model when other colleagues voiced skepticism or cynicism. Similar occurrences have been previously reported in the literature (Bernstein et al., 2007).

It should be noted, however, that it is also important to not rely entirely on a single champion. A team that includes broad representation of diverse perspectives should surround the champion. This ensures against an overly accepting champion and against champion turnover. At times, the enthusiasm of an champion can be so strong that they can be too quick to accept results! This can make face validation difficult. Therefore, when working with a strong champion, we need to ensure that the validation of our model is completed by the full team. In the event that the project champion leaves their current role, an engaged team can smooth the transition and avoid potential loss of contact, interruption, termination or transformation of the project.

Therefore, to increase the long-term impact of operational research, it is imperative that we proactively identify and seek out potential champions, work with them to see the benefits of OR in general as well as for specific applications and nurture the relationship long-term. This will help us to not only increase the number of operational research implementation successes, but also lead to larger, more impactful interventions over time.

2.1. Good result: strong champion

Cancer Care Ontario is an arms-length data analysis and policy advisor organization on all types of healthcare (which started with cancer and then grew). The director of planning saw the value of using operational research for province-wide planning/resource allocation. As such, he supported multiple projects over the years, including colonoscopy capacity planning, thoracic surgery location/allocation, and the endoscopy efficiency toolkit. This strong relationship not only provided senior level approval, but also resulted in a long-term partnership.

2.2. Poor result: no champion

NSERC funding was provided to model ontario family physician practice location/allocation and test incentives to encourage family doctors to work in rural Ontario (Graber-Naidich et al., 2015, 2017). While the work was interesting academically and resulted in several publications, we were unable to interest policymakers in our work. This push system of doing the work in isolation, and then attempting to garner interest in the results, is less effective than having an engaged partner from the start who can vouch for the work and is prepared to engage in, and support, implementation.

2.3. Mixed result: turnover

We applied for research funding to study patient flow in ten different Ontario emergency departments. We had the Medical Directors of ten emergency departments (EDs) agree to participate as part of our application. A year later, by the time we had the funding and the research team set up, five of the ten Directors had moved on, and no one knew what we were talking about. Fortunately, we were able to convince the new managers to allow us to proceed and support the work, but there was a significant start-up delay. We believe that this is not unusual in the industry.

3. Critical issue

In healthcare, senior management must focus on the most pressing issues facing them and prioritize resources accordingly. Lower priority projects in hospitals, for example, can get pushed aside when faced with a “burning issue” or crisis like a multi-day emergency department overcrowding problem, an infection outbreak, a bed capacity problem, or a recent high surgery cancelation rate. The focus is sharpened further when the issues are reported in the news or become a political priority. Therefore, operational research problems that address an urgent need, that have a clear deadline, and that require action, are most likely to result in implementation (Wilson, 1981). An operational research intervention that can address a current critical issue will be more likely to receive senior management backing, funding, resource support, and expedited data sharing. On the other hand, when the project is small and low priority there will likely be long delays getting data, required approvals, and securing stakeholder meetings. For example, undergraduate student projects are often “nice to have”, but not “mission critical”.

However, critical issues tend to need quick answers, so there may be limited time to build a rigorous or academically interesting model. This creates pressure to deliver a solution more quickly than may be practical (Jahangirian et al., 2015), or management may need to make a decision before the full analysis is complete (Bowers et al., 2012; Eldabi, 2009). (Many of us in the OR community have provided quick and dirty decision support tools in the wake of the Covid-19 pandemic.) We need to find ways to quickly deliver solutions to critical issues while not compromising the rigor of our work. Bowers et al. (2012) recommend the reuse of simulation models to speed up the implementation time when facing burning issues. We have had some success with a generic model that can be tailored to specific hospital processes and structure through inputs. The implementation still requires significant engagement upfront, but the development time is in weeks or months, not years.

3.1. Good result: critical issue

In 2011, the Saskatchewan provincial government declared that by 2014 no patient would wait for surgery for more than 3 months (based on 90th percentile). Victoria Hospital in Prince Albert determined that to meet these requirements, they would need the government to provide two million dollars funding to increase surgical capacity and add an additional orthopedic surgeon. In contrast, the government felt the hospital was inefficient with their use of resources and so could do more with what they already had. Since the clock was ticking on meeting this wait time pledge, the government contracted our team to analyze current operations and determine how to meet the wait time deadline.

We had a previously developed generic surgical simulation model that could be reused for this purpose. The model was designed to be tailored to the specific circumstance of an individual hospital through a detailed set of input options. We could therefore respond quickly to this need while still fully engaging the hospital team in populating the model with appropriate inputs to create a valid “as-is” scenario, and then experimenting with ways to meet the wait time targets. Our analysis demonstrated that the hospital did have some serious inefficiencies that our model was able to highlight. However, they did also require the additional funding and resources. The previous development of a generic model was therefore key to being able to respond quickly to a burning issue.

3.2. Poor result: no crisis

In 2009, we were asked by a senior Director in the Ontario Ministry of Health to create a system dynamics model of the provincial healthcare system (acute care, complex care, rehab, home care, long-term care) so that policy makers could estimate the effects of changes across the system and make informed, data-driven decisions for the full system of care (Esensoy & Carter, 2015; Essensoy & Carter, 2018). The potential to make an impact at the policy level is high and we had an internal champion, but we are still waiting for an urgent issue that motivates its use. Although the breadth and detail of the model is what makes it effective, it also means that the data requirements are large, so a critical issue is required to justify the effort required to populate and interpret the model.

3.3. Mixed result: fast burning issue

Following the successful implementation of our generic perioperative model at an Ontario hospital, we were asked to help fix a critical issue. A renovation was underway to build a new tower with additional ward beds and at the same time the hospital's emergency rooms were chronically overcrowded. The problem of “hallway medicine” was in the news in Ontario and in political discourse. Senior management asked if we could examine the medical side of the hospital just like we had with the surgical side and determine a solution for the emergency department overcrowding, while at the same time advising on how to best allocate new bed capacity in the medical wards.

While we had been able to move relatively quickly on the surgical side due to our existing generic model, we could not move sufficiently quickly to build a bespoke simulation for the emergency department and medical wards. By the time we developed a model, the hospital was focused on new crises, and many of the original team members had left. However, we were able to turn the model into a hospital-wide generic model and successfully use it elsewhere for another hospital that was renovating and expanding capacity (Busby & Carter, 2017, 2020). A third hospital expressed interest in using the same model, but never determined the pressing issue they were looking to fix, so although a few scenarios were tested for this hospital, none were implemented. So, the model was initiated by a critical issue, the fire burned too quickly at the first hospital, just right at the second, and was not strong enough at the third.

To take advantage of the resources that are made available for critical issues, OR practitioners can attempt to anticipate the next issue, such that some groundwork is already done when the burning issue rises to the surface. Critical issues often can be cyclical (e.g., managing the flu crisis) and organizations can face similar issues at different times (e.g., capacity crisis or expansion) so to some degree we can predict and prepare for these opportunities. Flexible generic or reusable models can be helpful in this respect as well.

4. Cultural insight

Much of what makes healthcare particularly challenging is the unique culture in healthcare. While it can be argued that healthcare is similar to any other organization or business in that it provides a service to customers, there is a great deal of additional complexity. Key challenges presented by the unique culture of healthcare are discussed below:

1. Limited Resources:

   There may be resistance in general to improvement projects as they can be seen as detracting from front-line work by diverting needed financial and human resources (Brailsford, Bolt et al., 2009; Jahangirian et al., 2015). For this reason, managers need to believe that the investment will clearly produce a worthwhile outcome in reasonable time (Harper & Pitt, 2004), and that outcome will ultimately have an impact on patient care. If this is not clearly the case, a project or investment will meet resistance. While doing things the same way they've always been done may not be the best option, it is often the least risky and the least resource intensive option. As discussed above, a critical issue can change this dynamic (Wilson, 1981). In such a scenario, there is benefit in even the perception that something is being done to improve the situation.

2. Distrust of Models:

Managers typically have a clinical background rather than business or engineering and have not been exposed to OR modeling in other industries. There is therefore often no internal modeling expertise, familiarity, or cultural acceptance of modeling (Jahangirian et al., 2015). There is also a perception that these tools cannot be applied to healthcare because patients are not "widgets" and medicine cannot be boiled down to simple procedures (Brailsford, 2005; Brailsford, Bolt et al., 2009). Many clinicians pride themselves on the complexity of their jobs and enjoy the challenge that brings. They will often cite the "art and science" of their craft and therefore resist having that simplified or distilled into concrete processes for a model that may recommend overly structured solutions.

As discussed in Brailsford et al., and Young (2015), clinicians typically view empirical evidence such as randomized control trials as the most convincing, whereas managers are typically convinced by historicist evidence such as anecdotes. Simulations on the other hand offer a third type of evidence – rationalist, where evidence is generated based on "theoretical constructs which embody rationally constructed arguments from explicit premises" (Brailsford et al., 2015, p. 1485). This third approach is often less convincing to clinicians and managers. This resistance to simulation can be expanded to apply to operational research models in general. The ability to convince stakeholders to view model outcomes as evidence is exacerbated, understandably, if the rationale for model design is not transparent, as may be the case for models constructed by the operational researcher in isolation.

In addition, there are many examples of models that have been presented to the healthcare community that were not based on the best assumptions. One poor example will color a decision maker's impressions of operational research for years.

3. Power Structure and Conflicting Incentives:

In many healthcare settings, particularly hospitals, there is no defined hierarchy and final decision maker (Naseer et al., 2009). Although stakeholder engagement is key to project success, the unique power dynamic in healthcare makes meeting the differing priorities and objectives of all stakeholders a significant challenge (Bowers et al., 2012; Brailsford, 2007; Eldabi, 2009; Harper & Pitt, 2004; Lagergren, 1998; Wilson, 1981). Glouberman and Mintzberg (2001) explain the complicated power dynamic in healthcare using the "Four Faces of Health Care" and Degeling et al. (2003) use a similar model to show these dynamics in the UK, Australia, and New Zealand. Managers, physicians, nurses, government, and other stakeholders have differing incentives, areas of expertise, and often conflicting goals. It will often be the case that any change will impact stakeholders differently and disproportionately, making it difficult to find an innovation that will produce an outcome perceived to be worthwhile by all stakeholders (Jahangirian et al., 2015). The lack of a clear decision-maker means that, rather than a final decision being made that balances the needs of stakeholders, these varied impacts need to be directly negotiated between stakeholders within a complex power structure.

Although most stakeholders have financial incentives and responsibilities, there is no market driving the organization toward a united financial or competitive goal - unlike in commerce or military applications where OR techniques are more widely implemented (Jahangirian et al., 2012; Naseer et al., 2009; Tako & Robinson, 2015). Instead, the united goal is toward a social "good". However, the perspective of each stakeholder differs on how that social good is defined and how it is best delivered. Physicians fiercely protect their autonomy, which they see as crucial to keeping the best interests of their patients separate from the best interests of the organization. For example, the physician does not want organizational priorities such as cost to impede or influence their clinical assessment or care recommendations. Physicians also resist being asked to "play god" by evaluating how the quality of care provided to one patient may impede on another. Instead, a patient in their immediate care is prioritized over one waiting for care (Wilson, 1981). On the other hand, managers may be more acutely aware of, and held responsible for, the negatively affected patients not yet in care (e.g., patients waiting too long in the emergency department waiting room or waiting for an appointment at home). The government, in turn, will be more sensitive to media and public pressures to create and sustain an effective healthcare system.

If there is existing internal conflict between stakeholders on the proper direction to take, operational research analysis can offer a neutral third-party perspective. However, this only works if this neutrality is perceived by all stakeholders (Harper & Pitt, 2004). A lack of neutrality can be perceived if the team has been invited to participate by one side of a conflict, or language is used that can be misinterpreted. In one project we completed, the model would cancel a scheduled surgery if there was not enough time remaining in the day for it to be completed. When summarizing the results using "not enough OR time" as the reason for cancelation, this label was perceived to be biased by a manager. Instead, she suggested "overscheduling cancelation" since the first implied that more OR time should be added whereas the second implied that less surgeries should have been scheduled. Ensuring the perception of neutrality can be challenging but is important to ensure all stakeholders trust the process. Of course, operational research projects normally have a sponsor who initiated the engagement and pays the bills, so "objectivity" is often a tough sell.

4. Silos:

Most healthcare organizations operate in silos on many levels. As discussed, there are silos based on roles within the organization, but there are also silos between departments within an organization (Vanberkel et al., 2010) and between healthcare sectors such as hospitals, home care and long-term care. This prevents stakeholders from having a clear understanding of how their decisions affect other departments or sectors, expanding the potential number of stakeholders required on the modeling team (Brailsford, Bolt et al., 2009). In addition, organizations tend to see themselves as unique among their peers (urban vs rural hospital, teaching vs community hospital, etc.), and therefore, as noted in Brailsford (2005) and Brailsford (2007) a "not invented here" mentality is common, making model reuse, and therefore wide dissemination challenging.

Although the cultural dynamics add challenges for an operational research practitioner, we may also be in a unique position to add additional value by giving each stakeholder insight into the full system and taking all concerns into consideration (Eldabi, 2009; Eldabi et al., 2002,; 2007; Harper & Pitt, 2004). This may explain why simulation modeling is among the most popular and growing operational research techniques employed in healthcare (Brailsford, Harper et al., 2009; Fakhimi & Probert, 2013). When using simulation models, we have found that testing suggestions from all stakeholders in "what-if" scenarios make people feel that they are being heard and not "railroaded" and allows ideas that don't do as well as expected to be examined and then dropped. Without this, some stakeholders will doggedly stick to promoting their idea and be unwilling to move on or discuss other options. In several hospitals, surgeons have been convinced that if turnovers between surgeries are completed more quickly, operating room throughput will improve significantly. This has generally been shown to be untrue in multiple hospitals unless the ratio of surgery time to turnover is very low, however, we often include this scenario when it is suggested. Once presented with the results, the surgeons accept the conclusion, and engage in other creative ideas for increasing throughput.

Additionally, bringing stakeholders together to build an operational research model can improve communication and understanding between stakeholders, (Baldwin et al., 2004; Bowers et al., 2012; Eldabi, 2009) and provide a wider appreciation of the interdependent dynamics of the full system (Eldabi, 2009; Jun et al., 1999; Lagergren, 1998). Involving managers and clinicians in model building also forces them to purposefully articulate and critically evaluate current processes (including many workarounds and "how we actually do things" that may not be captured in existing process documents). This process of building the model with the stakeholders can also highlight areas for improvement even before the model is fully constructed (Bowers et al., 2012; Eldabi, 2009). In our experience, we find that there are at least as many proposed solutions to a problem as there are participants. Many of them will not work, but the correct answers are usually found within the list.

So, the challenge for the operational research practitioner is to be able to create a solution that all stakeholders agree is optimal. They must understand the varying incentives and goals of physicians, nurses, administrators, finance managers, government, decision support/IT, and patients and be careful to present themselves as completely neutral. Ultimately, the best way to achieve this and meet the challenges presented by the healthcare culture is to be as immersed as possible in that culture, while continuing to maintain third-party neutrality, so that we understand the underlying conflicts, incentives, power dynamics and work processes.

In our experience, when we are looking for a solution to a problem, we need to be aware of the concerns and objectives of each of the stakeholders. If a proposed solution is good for patients and doctors, but creates extra work for the nurses, it will fail. It has to be better (or neutral) for everyone. Fortunately, in the current healthcare environment, it is virtually always possible to find a solution that is better for everyone.

4.1. Good result: optimal solution for all

A perioperative simulation was used in an Ontario hospital to evaluate revisions to the surgical schedule with the goal of balancing demand for beds over the week. Smoothing weekly demand was important for surgeons because on days where beds were full, their surgeries would routinely be canceled. This had a negative impact on their time, their finances, and the quality of their patient's care. Nurses in the operating rooms and in wards were also negatively affected by the workload imbalance. Administrators were concerned with expensive operating rooms being underutilized. Both the patient suffering a last- minute surgical cancelation and patients further down the waiting list had delayed care. This offered an opportunity to find a solution that would improve the situation for the many stakeholders involved.

Ultimately the simulation revealed that there were more than enough beds allocated for surgical patients, but surgical beds were routinely being assigned to medical patients early in the week when not being fully used by surgical patients, and these beds remained occupied later in the week when surgical patient needs increased. It was concluded that some surgical beds could be permanently reassigned as medical beds, since clearly the demand for medical patient beds outstripped the supply. In exchange, the remaining surgical beds were reserved exclusively for surgical patients. The model was able to demonstrate to the surgeons that they could give up some beds to medical wards without risking surgical cancellations, and medical physicians could see that with the additional beds they would not need to off-service patients to surgical beds. Without the simulation, physicians on both sides of the hospital would have been extremely reluctant to agree to these changes, but the simulation let them see that they could both benefit. The solution was piloted successfully and ultimately the change was fully implemented.

4.2. Poor result: implementation required on-going work processes

Patients waiting for elective orthopedic surgery can wait several months with little indication of when they will get to the top of the wait list and receive their surgery. Surgeons are unable to precisely estimate the date as there are several complicating factors including the arrival of more urgent patients to their list, interruptions to their surgical schedule and cancellations requiring rescheduling. Since they are not able to accurately predict the surgery date, most surgeons tell patients that they are "on the wait list" and will be contacted closer to the date. This undefined waiting period is mentally taxing and often requires patients to put their life plans on hold indefinitely.

In response, a simple Excel tool was developed to estimate patient wait time for surgery. When surgery was first planned, a wide window (three weeks) would be given for the surgery date. As the date grew closer, the estimate would be updated with each estimate offering a more precise window for the estimated surgery date. While this was still not a precise surgery date, it would allow patients to make plans around vacations, post-surgery care, and other activities.

The patient was the clear beneficiary in this case. For the surgeon, it added a new layer of transparency and accountability. There could be perceived risk of needing to explain and justify incorrect estimates to dissatisfied patients. They may have felt that making no commitment was preferable to making an incorrect commitment in these cases. Therefore, some resistance from surgeons was expected. However, surprisingly, the resistance came instead from the schedule assistants in the surgeon's office due to the ongoing need for extra data entry. As a result, the model was not implemented. The impact of interventions on all stakeholders was not fully anticipated, which thwarted the implementation.

4.3. Mixed result: misaligned objectives and communication

A hospital in Toronto was renovating and trying to decide how many operating rooms they required for the future. A manager in charge of planning at the hospital requested our help, using our generic perioperative model, to provide a non-biased, third-party review to determine the number of operating rooms that should be constructed. The Steering Committee had multiple stakeholders including hospital administrators, and the chief of surgery.

The chief of surgery was advocating for more ORs and was not interested in a third-party analysis. He felt strongly that we could not sufficiently capture the complexities of surgical scheduling and flow and believed that there was already ample evidence to support his case. As a result, he strongly resisted the model from the start.

In addition, we made the mistake of saying that we needed to complete a “validation” stage where we populated the model with current data from their hospital to check the model outputs against current actual outputs. While for us, this was an exercise in ensuring we had correctly captured their local processes and that the data was accurate, he believed we were saying that we were evaluating the model itself to see if it worked. He was not prepared to allow such a crucial decision to rely on what he perceived to be an untested academic exercise. Although we tried to explain what we meant, the use of the term “validation” convinced him that there was no value in our model.

Despite this we did go ahead and produce an as-is version of the surgical flow. While the chief was impressed by how accurately it was able to predict their throughput, he still did not fully trust the model’s predictions. We produced a series of scenarios that we turned over to the planner, but we did not have insight into the final decision-making process so were unable to assess whether our work had an impact.

5. Data quality

Clearly models will only be as good as the data that feeds them. Given the volume of data collected in healthcare, it is surprisingly difficult to acquire good quality data for most operational research problems. This can stall or limit model design, limit validation and verification, and therefore ultimately hamper model implementation (van Lent et al., 2012). Data is a commonly cited problem when examining the challenges of modeling in Healthcare (Brailsford, 2005; Harper & Pitt, 2004; Tako & Robinson, 2015). There are few reasons why data quality is such a challenge:

1. Data Availability and Applicability:

   Data is not collected with operational improvement in mind since many organizations do not have internal process analytics teams (although they are increasing) and patient flow reporting is not required. This means that data is generally not collected on patient flow. Instead, data is collected for clinical purposes, accounting, government/public reporting, and patient health records (legal support). As such, operational research often makes do with data collected for an alternate purpose that can serve as an adequate but imperfect approximation. In some cases, even when relevant patient flow data is collected, repurposing isn’t possible. For example, in one hospital emergency department the location of every patient was tracked, but when they moved, the previous location was overwritten. The purpose of the collection was to locate patients, not to analyze patient pathways through the emergency department.

   In addition, things often change quickly in healthcare, so while it is ideal to collect data over a long timeframe, this increases the number of structural, process flow, and data collection changes over the collection period (Baldwin et al., 2004; Eldabi et al., 2002).

2. Data Accessibility:

   In some situations, the data is tracked and saved, but is difficult to access either because it is not tracked electronically (tracked on paper, faxed) (Brailsford, 2005; Harper & Pitt, 2004) or because it not clear where the data is stored. In one example, for an inpatient simulation, we required data on the movement of patients between wards. The internal analysts on the team reasoned that the data had to be stored electronically in case there was a need to trace the movement and interactions of a patient found to have an infectious disease. Although they reasoned it existed, nobody on the team including decision support initially knew where the information was stored.

   Even when the data is tracked and stored electronically, and the stored location of the data is known, it may not be easily extracted. For example, data captured electronically through scanning, or in freeform makes searching, sorting, and processing the data impractical.

   Finally, privacy regulations and lengthy research ethics approvals can make data difficult to access (Brailsford, Bolt et al., 2009; Naseer et al., 2009). Privacy becomes a bigger concern when data stored in multiple databases must be linked using a patient identifier. Research ethics approvals required to access data, are geared toward clinical research and as such are difficult to apply to operational research requests, leading to a long and difficult process. As a result, there is pressure to identify data required as early as possible in order to quickly initiate this process. Future amendments to this data request will also delay the project.

3. Lack of standardization and database links:

   Lack of standardization across healthcare organizations or even across hospitals in the same jurisdiction makes it difficult to do either system-wide analysis or to reapply data processing techniques when transporting/reusing models. If the required information is stored in multiple databases or subsystems that either need to be linked or do not communicate at all, matching between databases is difficult. For example, in one project, electronic ambulance data was not linked to electronic ED data, so probabilistic matching was used to recreate patient pathways.

4. Incomplete or erroneous data:

   Because of how and why data is collected, the quality of the data that can be obtained may be very poor. In many cases key information, such as timestamps, are simply missing. In other cases, the information is entered but is inconsistent with other data (e.g., timestamps indicate that activities started after they finished) (Harper & Pitt, 2004). Finally, the data that was included and excluded when pulled from a database could be incorrect. For example, in one project, mental health patients were missing from the initial data set because they were stored in a separate database for billing purposes. In another example simulating an emergency department, the data indicated an unrealistic number of patients who were all discharged at 11:59 PM. One assumes that the patients left earlier, but the timestamp was entered at nursing shift change. We have also observed that some systems collect data because it “might be useful sometime to someone”. Any data that is not actually used regularly will almost always be wrong.

When data is imperfect or lacking, there are mitigating strategies that can be used to ensure models are as accurate as possible.

First, it can be tempting to use expert estimates in place of data when hard data is unavailable or cannot adequately represent the situation without context. However, these estimates are not always dependable and can result in poor outcomes (Wilson, 1981), unless there is secondary data that can be used to validate the estimates. There is a natural tendency for people to overweight exceptions or situations that are most impactful. As an example, estimates of average occupancy tend to be high because overcrowding has an outsized impact on healthcare workers dealing with these stressful situations. Clinicians are more likely to take note of the 3–4 day stretch of overcapacity than the 3–4 day stretch where they are under-capacity. This can also make face validation difficult in the absence of other data to guide instincts. We can compensate to some degree by asking for multiple data points rather than an average. For example, asking a family doctor to estimate the average time for a patient office visit may be challenging. However, asking them how long they spend with a few common types of patients may produce better results.

Second, it is important when using data that was not collected for the purpose of the operational research study, to understand when, how, by whom, and for what purpose the data was entered at the time it was collected. This will provide context and insight on the possible inaccuracies in the data and its suitability for use in the current study (e.g., Is the time the patient enters the OR automatically tracked and timestamped by an RFID, or is it recorded in real time by an OR nurse, or is it estimated and entered manually at some point in the day? Do they use the actual time or the scheduled time and duration?) Therefore, having internal technical support from people who really understand their data is invaluable.

Finally, we build in data validation checks before testing the data in our models and keep available data and data quality in mind when setting objectives for our models. The accuracy and useability that can be expected of the proposed model, given the quality of the data available, must be clearly communicated to the stakeholders and discussed when setting goals and expectations for model outcomes.

5.1. Good result: great data

We did an analysis to predict the workforce requirements for cardiac surgeons in Canada (Vanderby et al., 2010; Vanderby et al., 2014). We had access to years of data on every cardiac procedure, the age of every cardiac surgeon in the country, access to residents/fellows who wanted jobs and the ability to execute surveys. This contrasts with a similar project currently underway analyzing the General Internal Medicine physician workforce in Ontario. In that case, it is difficult to determine what they do, who they are, and where they work. Moreover, demand is impossible to estimate.

5.2. Mixed result: reasonable patient data, poor process inputs

Our generic perioperative model has been implemented in fifteen hospitals. The hospitals tell us their OR schedule and their operational rules, and we populate the model with patients from their historical data. The patient data is repurposed from data they collect for reporting to the government and from operation room data that records details on each surgery (surgeon, start time, end time, operating room). While the data represents patient movements reasonably well, the inputs required on the operating structure and processes rely on the information reported to us by the internal team of clinicians and managers. For example, the process rules and assumptions include: the operating room schedule, rules regulating when overtime is permitted, the assumption that surgeries start when the OR opens and that new surgeries do not start after the OR closes etc.

On first pass, once data input errors have been eliminated, results of our as-is scenario never match reality. Invariably, this is because the official rules and parameters that we are given to populate the model are not followed as written. We then discuss what actually happens in practice and either adjust the model inputs (in cases where it is recognized that the practice deviates from the official rules but is a known and approved exception – e.g., cancer surgeries having more flexible overtime rules) or simply identify the reason for the gap (in cases where the rules are violated but should not be).

For example, in some cases it was discovered that some surgeons routinely start much later than the official OR opening time despite being staffed for opening time. The inputs for this are not adjusted since this is not the desired state, not a result of the larger process, and has no practical advantage. Instead, we quantify the gap in the as-is model to determine if the model is otherwise representative. In another case, it was discovered through as-is modeling, that surgeons were using time reserved for urgent patients to do elective surgery. Similarly, when modeling a reduced summer surgical schedule, the as-is analysis revealed that the surgical volumes had not reduced as much as the summer schedule indicated it should. It turned out that extra surgery time was routinely being added in on an ad hoc basis without consultation with the wards who were staffed for a reduced surgical schedule.

In these cases, a debate is sparked between clinicians and managers as to the proper approach – in which case the alternatives may be added to future state scenarios. We view the model as providing quantitative support to situations that managers probably knew about but could not demonstrate. Regardless, there is always extra effort required to work through discrepancies with internal teams to determine what "really" happens. We cannot simply plug in the data and move ahead as the data always tells an incomplete story.

5.3. Poor result: data requirement too large

Our team's ambitious system dynamics model of the Ontario health system required an enormous amount of data to capture the intricate interactions across the system. The goal was to estimate the impact of major funding/capacity changes made at the policy level. Years of data was required to populate the model, but this necessarily included data drawn from before and after other major policy changes making it hard to determine the appropriate "as-is" state that best matched the time frame for data. In addition, for many elements within the model, data was unavailable, so the model mostly relied on expert opinion gathered from multiple expert panels across different sectors. The data gathering method was extremely time consuming and data intensive. While the original request for the model was to have something policy makers could have on a desktop and experiment with, the reality was that there were only a handful of levers that policy makers were interested in and too many details that would have to be updated to keep the model relevant over time. Interpretations of results was also not straight forward making this type of desktop non-expert operated model difficult to implement.

6. Expectation management

There is a misconception about what operational research models can and can't do, which leads to unrealistic expectations (Bowers et al., 2012; Eldabi, 2009). Therefore, expectations management (van Lent et al., 2012) and alignment of objectives (Jahangirian et al., 2015) between the client and modeller are key to implementation success. Often, a misalignment on model expectations occurs because clients are looking for predictions of the future whereas models are scenarios based on a given set of assumptions, i.e., if the following (long list of) assumptions are all true, then the modeling outcome appears highly likely. We do not predict the veracity of the assumptions, but we do try to ensure our models are close to reality once we agree on the assumptions. We need to ensure that everyone is on the same page and not assume that they "get it". This belief can lead to misunderstandings about assumptions during model building, disappointment with solutions, or overreliance on model predictions. It is easy to assume that everyone is on the same page and understands how the models work until, sometimes too late in the process, it becomes apparent that is not the case. Therefore, time needs to be invested upfront in ensuring that the conceptualization, capabilities, and limitations of the model are explicit and reinforced early and often.

Healthcare managers and clinicians are typically highly capable leaders who like to be able to dig in, test, and explore the model on their own, so it is also a common expectation that clients will be able to keep a user-friendly version of the model that they can adjust independently and over time. However, as noted by Bowers et al. (2012), this affects model design. This can include simplifying the inputs and reducing the complexity and flexibility of the model. In addition, over time, underlying assumptions, data, and questions asked of the model will likely change. This is particularly true for simulation models, that tend to capture complex interactions but are built for a specific purpose that dictates model assumptions and simplifications. So, unless the model user is well versed in the current assumptions, understands the boundaries of the model's usability, knows how to update underlying data, and how to validate the model over time, there is a risk that models designed to be used on-going by non-experts will become invalid over time. In addition, results often require analytical interpretation (Lagergren, 1998) based on intricate knowledge of the model workings, adding a further challenge to on-going use by a non-expert. These barriers have prevented operational research models from becoming embedded in healthcare decision making and therefore have blunted their potential impact (Barlow & Bayer, 2011; Eldabi et al., 2007).

To keep things simple, manageable, and accessible, clients often desire a simple model that can address complex problems. While we always strive to keep our models as simple as possible, there is also a danger in them being too simple (Eldabi, 2009). For example, in Ontario, a simple linear regression model, used to estimate nursing volumes in the province estimated that everyone in Ontario would be a nurse by 2050! The missing context was that cuts during the 1990s led to efforts to close the gap after 2000, resulting in a steep increase that would not be sustained. The straight-line approximation forecasting into the future therefore produced a specious outcome. Other examples include use of a linear fit on the incidence of disease. For diseases that have been decreasing recently, the models will predict that the disease will be eradicated and go negative. For some problems, linear models make sense, but we need to be careful about our assumptions. Lagergren (1998) discusses the balance between capturing the complexity of health care systems while simultaneously keeping models as simple as possible. As Einstein famously said, "For every complex question there is a simple and wrong solution". Therefore, we need to ensure our models are "as simple as possible, but no simpler."

Interestingly, machine learning models that are typically far from simple representations, have caught the attention of many healthcare clinicians and managers. More and more requests are being made not just to address a current problem, but to address it using machine learning. It would be interesting to understand why machine learning has such a strong appeal that has not been enjoyed by other areas within operational research. The difference may be the perception that machine learning offers the chance to decisively predict the future in a way that the human brain cannot match – although the model itself is complex, the idea is simple. It may also be that it feels more familiar to many who are comfortable with regression analysis and can see this as a much more sophisticated extension of that concept. So again, while they don't understand the details, they are comfortable because they understand the high-level concept. However, it is also true, that many perceptions of machine learning, its current capabilities, and its limitations are flawed, leading to erroneous conclusions about how it can be used and the reliability of the results.

Ways to mitigate these challenges include working to increase the internal operational research capabilities of healthcare organizations (Monks, 2016; Wilson, 1981); choosing and creating appropriate tools for use by non-experts; partnering with national and regional healthcare improvement organizations to develop tools that can be widely distributed (Barlow & Bayer, 2011; Bowers et al., 2012; Brailsford et al., 2013), and embedding researchers in healthcare organizations (Marshall et al., 2016). Barlow and Bayer (2011) describe several large-scale partnerships between modellers and leaders in the NHS aiming to bridge the gap between expert and non-expert. We routinely embed student researchers in healthcare organizations and have been able to hand-off our generic perioperative model to two Ontario hospitals once engagement with the student ended. The model was used extensively over time by internal experts with a background in modeling. However, when the internal experts who had been trained on the model left the organizations, the model was no longer used.

6.1. Good result: managing expectations

The engagement with the Saskatchewan Ministry of Health and Victoria Hospital in Prince Albert described in section 3.1 above is an excellent example of successful management of expectations. The Ministry believed that the hospital was very inefficient, and the hospital believed that they needed $2 million from the Ministry. Using our perioperative simulation model, we were able to convince both parties that the other side was correct and that they would need to change what they were doing. In order to accomplish this, we needed to convince both parties that our model was a reasonable representation of reality. We worked closely with the Operating Room administrators and staff to understand their perspective before finally presenting our analysis to the surgeons and the Ministry leadership.

6.2. Poor result: model complexity higher than expected

The original idea for our Ontario Health System model (Esensoy & Carter, 2015; Esensoy & Carter 2018) came from a policy maker in the Ministry of Health who dreamed of having a simple model on the desktop of policy analysts so that they could assess system level changes and avoid unforeseen consequences elsewhere in the system. In hindsight, the project team probably did not fully appreciate the sponsor's expectations. We were focused on creating a model that was necessarily complex, requiring a great deal of hard and soft data inputs as well as contextual results interpretation. The model was too complex to be user-friendly. Once a particular decision problem was determined, it would be possible for an experienced modeler to create an interface that allowed a general user to experiment with a subset of levers and display a few relevant output variables. Therefore, while we could use the model to allow non-experts to experiment within a very narrow band, they still needed to define their experiment clearly with the help of an expert. In the end, we kept asking them for a current major issue, and they kept bouncing back to ask us what questions the model could answer.

6.3. Mixed result: counterintuitive model

We were asked by Bone & Joint Canada to predict the needs for orthopedic surgeons several years into the future. Although the quality of the available data was not high, we were able to predict a major shortage of orthopedic surgeons. We announced our findings to Bone & Joint Canada, but the reception was confusion. The Globe and Mail (a major Canadian newspaper) published an article two weeks earlier declaring that orthopedic surgery graduates could not get jobs. In fact, both were correct. At that time, the wait lists for orthopedic surgery were long and growing faster than supply. The government recognized the problem and provided additional funding to hospitals for specific priority procedures: hip and knee replacement, shoulder surgery and spine surgery. However, they did not provide funding for foot and ankle, head and neck or hand surgery. Orthopedic residents specializing in non-priority areas were indeed having a difficult time finding jobs. However, the conflicting top-line conclusion that we needed to train more orthopedic surgeons while graduates couldn't find jobs understandably confused the message.

7. Discussion and conclusion

We have outlined the five key areas we believe, based on our experience, are fundamental to successful implementation of operational research models in healthcare: an internal champion, a critical issue, healthcare cultural insight, Data quality, and expectations management.

It is instructive, as a simple case study, to consider each of these areas with respect to the Covid-19 pandemic. We clearly have a crisis, and there are plenty of champions (and funding sources). However, there is essentially no data from previous epidemics, the culture has experts in every domain arguing their position at length with very little consensus, and public expectations of the modeling efforts are unrealistic. The models that are shown regularly are typically based on SEIR models with relatively simple assumptions. OR has not taken a lead role.

While we have examined each of these five key elements independently it is clear there is significant cross-over between them as well. For example, a strong champion inside the organization can galvanize resources to find or collect better quality data, can ensure expectations are aligned, manage internal power struggles, bring in operational research teams early to tackle a critical issue, and keep focus on a project over the long-term even if the urgency fades. Likewise, robust data sources can make it easier to meet short timelines required for critical issues, convince people that the model works as intended, while helping to build future champions. A thorough understanding of, or immersion in, the healthcare culture by the operational research team can help to avoid miscommunications and misalignment of expectations, understand the priorities of each stakeholder in the organization and better understand the context in which the data being used is collected. Designing and creating models that are transparent and accessible to decision makers will not only help with managing expectations but will also help to integrate modeling into the healthcare culture, create awareness for the necessity for reliable patient flow data, and increase the number of potential champions. Therefore, as well as being individually important, there is also clearly synergy between each of these five elements. Being able to excel in one of these five areas can make it easier to excel in or mitigate issues in the other areas.

Over the long term, the operational research community can help build an environment that will be more conducive to innovation in the future and to contribute toward improving the five elements outlined. This can be achieved by building trust with small successes (increase champions), investing in an understanding of the drivers of healthcare culture by immersing researchers in the organization where possible (increase cultural insight), promote hiring of operational research graduates to internal positions in healthcare organizations (increase champions, cultural insight, expectation management), lobbying for better patient flow data to be collected and standardized (increase data quality), and exposing future healthcare leaders to operational research concepts as part of their education (increase champions, data quality, expectation management).

Focus on these five elements through short-term and long-term strategies will move us closer to having a significant and lasting impact on healthcare. Over the decades it has become easier to find champions, we have been able to develop tools to position ourselves to quickly address critical issues, we have become more embedded in healthcare organizations, data quality has improved and, we have educated students who take up positions in healthcare organizations at a variety of levels and roles. We are therefore optimistic that, with these five elements in mind, operational research will continue to have a larger and larger impact on healthcare.

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